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FORECASTING OVERHAUL OR REPLACEMENT INTERVALS BASED ON ESTIMATED SYSTEM FAILURE INTENSITY

by

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December, 1994

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by

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ABSTRACT

System reliability can be expressed in terms of the pattern of failure events over time. Assuming a nonhomogeneous Poisson process, and Weibull intensity function for complex repairable system failures, the degree of system deterioration can be approximated. Maximum likelihood estimators (MLEs) for the system Rate of Occurrence of Failure (ROCOF) function are presented. Evaluating the integral of the ROCOF over annual usage intervals yields the expected number of annual system failures. By associating a cost of failure with the expected number of failures, budget and program policy decisions can be made based on expected future maintenance costs. Monte Carlo simulation is used to estimate the range and the distribution of the net present value and internal rate of return of alternative cash flows based on the distributions of the cost inputs and confidence intervals of the MLEs.

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LIST OF ACRONYMS, SYMBOLS AND/OR ABBREVIATIONS

ACRONYMS:

ATLASS	Asset Tracking Logistics and Supply System
CEC	Combat Essentiality Code
CM	Corrective Maintenance (Unscheduled)
DMA	Depot Maintenance Activity
ERO, EROSL	Equipment Repair Order, Equipment Repair Order Shopping List
ESP	Extended Service-Life Program
FMECA	Failure, Mode, Effects and Criticality Analysis
FMF	Fleet Marine Force
HMMWV	High Mobility Multi-purpose Wheeled Vehicle
HPP, NHPP	Homogeneous Poisson Process/ Non-Homogeneous Poisson Process
IID	Independent Identically Distributed (random variable)
ILSD	Integrated Logistics Support Directorate
IROAN	Inspect and Repair Only As Necessary
IRR	Internal Rate of Return
MCLB	Marine Corps Logistics Base
MDAC	Maintenance Data Analysis Center
MIMMS-AIS	Marine Corps Integrated Maintenance Management System - Automated Information System
MLE	Maximum Likelihood Estimator
MRP	Material Requirements Planning
MTBF	Mean Time Between Failures
MUC	Material Usage Code
NPV	Net Present Value
PEI	Principal End Item
POM	Program Objectives Memorandum

R&E	Replacement and Evacuation (Program)
RAC (1)	Reliability Analysis Center, IIT Research Institute, Rome, N.Y.
RAC (2)	Regional Activity Code
RASC	Regional Automated Service Center
ROCOF	Rate of Occurrence of Failures
SASSY	Supported Activities Supply System
SDC	Sample Data Collection
SPM	Scheduled Preventative Maintenance
TACOM	Tank-Automotive Command (U.S. Army)
TBF	Time Between Failures
TTSF	Total Time to System Failure
TM	Technical Manual
TWVULDP	Tactical Wheeled Vehicle Useful Life Determination Program
UM	User's Manual
USMC	United States Marine Corps

SYMBOLS & VARIABLES:

α	Confidence coefficient, i.e. $(1 - \alpha/2)$.
β	Weibull distribution slope, or shape parameter.
$E[N(t)]$	Expected number of failures during the interval (0, t).
$f(t)$	Probability density function.
$F(t)$	Cumulative distribution function.
$h(t)$	Hazard rate; peril rate.
K	Counter for number of repairable systems.
λ	A constant of the ROCOF
L_e	Life expectancy of a repairable system.
M_q	General counter used to express the total number of system failures.
N_q	Specific counter used to express the total number of system failures for either failure truncated or time truncated samples.
$R(t)$	Reliability of a repairable system at time t.
$\rho(t)$	Rate of Occurrence of Failures under NHPP; $\rho(t) = \lambda\beta t^{\beta-1}$ assuming system failures follow a Weibull probability distribution.
T*	Optimum Overhaul/replacement interval.
U	LaPlace test statistic for trend in failure arrival times.
$V(t)$	Expected number of failures in the interval (t, t + dt) where $V(t) = E(N(t + dt) - N(t))$

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...beware of mathematicians and all those who make empty prophesies. The danger already exists that the mathematicians have made a covenant with the devil to darken the spirit and to confine man in the bonds of Hell.

St. Augustine

I. INTRODUCTION

A. PURPOSE

The purpose of this thesis is to combine system reliability theory with observed equipment failures and maintenance costs in order to make better informed overhaul policy decisions for Marine Corps ground combat equipment[1]. Techniques currently used by the Army and USMC for computing the economic useful life of ground combat equipment assume a linear relationship between cost and age or usage (US Army TACOM, 1985). Systems reliability theory provides techniques for estimating linear and non-linear failure probabilities which can be used to predict how long equipment will last. Based on field data, we can compute the expected number of system failures over specified intervals, and associate expected costs with the failures to determine optimal maintenance policies and overhaul intervals. This thesis presents a model that is designed to give decision makers, such as the Integrated Logistic Support Directorate (ILSD), a more informed method for determining annual depot level overhaul requirements based on the material condition of the equipment fleet and a reliability projection about its remaining useful life. The approach uses existing equipment historical maintenance data which is readily available through the Maintenance Data Analysis Center, Marine Corps Logistics Base, Albany, Georgia, together with the IIT Research Institute, Rome, New York.

B. BACKGROUND

In many instances, it has been shown that rebuilding principal end items of equipment (PEIs) costs much less than buying new. For example, during 1986, the Marine Corps Depot Maintenance Activities rebuilt M60A3 battle tanks at a unit cost of $186,000 as opposed to the acquisition cost of approximately $1.3 million (Boak, 1988). The decision *when* to overhaul equipment is made using a break-even analysis of the basic cash flow alternatives, namely; 1) "do-nothing," meaning continue to perform field level, or "minimal" repairs when the system fails, 2) overhaul, or 3) buy new. When the buy-new option is not a viable alternative due to program funding constraints, the issue of

[1]The term "overhaul" in this thesis implies both depot rebuild programs, and the "Inspect and Repair Only As Necessary" (IROAN) concept.

overhaul intervals must be addressed. Optimal overhaul intervals are determined by minimizing the total expected cost of ownership over the life cycle of the system (Ascher and Feingold, 1984).

Currently, overhaul/rebuild intervals for Marine Corps PEIs are recommended by the contractor during the system acquisition phase (Boak, 1988). While these design estimates are likely to be accurate, a comparison based on actual equipment usage and maintenance data several years after the system has been in use may provide more meaningful intervals (Blanchard, 1992). This comparison might be thought of as a check, or a "tracking signal," to the contractor's estimate. The time to overhaul based on system deterioration may be different than the initial estimates, and provide an opportunity for cost savings in overhaul programs. The techniques provided in this thesis give a quantitative "snapshot" of where a PEI is in its material life cycle, which is then used to predict future failure probabilities. Knowing the expected failure profile for a system, policy decisions can be made about maintenance and overhaul intervals.

C. BENEFITS OF THE STUDY

The principal motivations for this thesis include:

1. The Need for Quality Information in Resource Allocation Decisions

DoD is faced with downward budget trends, but must continue to maintain high levels of operational readiness to meet the conflicts created by a turbulent world environment. In order to meet mission requirements, optimum use must be made of equipment resources, by applying analytic techniques to decision making and planning. Accurate information is needed to make cost-effective decisions about maintenance policies.

In some cases, it may not be economically desirable to replace low quantities of (repairable) equipment systems, due to excessive startup and production costs associated with low production quantities. In that situation, it may be more cost-effective to overhaul or "rebuild" the existing repairable systems (US Army TACOM, 1985). The decision when to overhaul/rebuild a repairable system is typically done using break-even analysis and Net-Present-Value (NPV) Cash-Flow techniques (Blanchard, 1992). However, in order to conduct a meaningful NPV analysis, future expected costs are required. Much of the literature in overhaul/replace decision-making assume linear maintenance cost models as the system ages (Perry, 1967). For example, the US Army Tank and

Automotive Command (TACOM) has an extensive Tactical Wheeled Vehicle Useful Life Determination Program (TWVULDP) which recognizes that system reliability decreases with age (implying that failure rates increase with age), however their maintenance cost model uses linear relationships. This thesis shows that the failure rate of deteriorating systems is not always linear, and provides an alternate approach to predict costs associated with expected failures.

2. Improved Marine Corps Overhaul/Rebuild Planning Criteria

The model presented in this thesis gives budget and program planners a way to characterize quantitatively the status of equipment in their life cycle using existing historical maintenance data. The Marine Corps uses several conflicting sources that provide planners with estimates on when to conduct depot level overhaul or replace ground combat equipment systems. Maintenance management planners refer to a technical instruction entitled "Replacement and Evacuation (R&E) Criteria; U.S. Marine Corps Equipment" (TI-4710-14/1, 1988). The R&E technical instruction provides usage criteria that determine when an item may become due for depot level overhaul/rebuild. Input from the Fleet Marine Force owning units (based on the TI-4710 criteria) is the primary document that drives the master work schedule requirements at the depot maintenance level. Overhaul intervals for the R&E program criteria come from contractor recommendations. The differences in useful life estimates can be quantified for the M998 High Mobility Multipurpose Wheeled Vehicle (HMMWV), which is the system analyzed in the case study presented in this thesis.

The TI-4710-14 gives 90 months (7.5 years) or 20-48,000 miles (peacetime usage) as the criteria for nomination of a HMMWV for depot maintenance. In contrast, the Marine Corps Cost Factors Manual (MCO P7000.14K, 1991), used by budget planners, program managers and activity comptrollers indicates a 48 month (4 years) "useful life" before rebuild for the HMMWV. The U.S. Army TACOM TWVULDP Modernization Plan estimates a fourteen year useful life for the HMMWV, which also is used by Marine Corps tactical wheeled vehicle Program Managers. Another source, the *US Marine Corps Concepts and Issues 1994,* indicates a seventeen year HMMWV useful life that can be extened to 30 years through an extended service life program (ESP). Of course, overhaul versus buy new decisions are not made based on single estimates in such publications, but through detailed cost analysis. Clearly, there is a need to refine some of the numbers used in the assumptions for the cost models, particularly the range of useful life of our combat equipment systems.

Further the opportunity cost of performing an overhaul or replacement too early in the system life cycle, given that a system has considerable "useful life" remaining, may not be acceptable. This thesis provides an alternate approach that can complement these sources and provide additional clarifying information with which to make decisions.

3. Provide Accurate Master Work Schedule Requirements for POM Input

Budgeting and scheduling overhaul requirements for the five year Program Objectives Memorandum (POM) is a highly uncertain process. Rebuild requirements described above must be translated into POM data, as well as the Depot Maintenance Activity (DMA) Master Work Schedule for production operations in the intermediate term. Accurate input data is vital to reducing variability in budgeting and production schedule planning. Better forecasting data can allow for Material Requirements Planning (MRP) to be done which could radically improve the quality of Depot Maintenance production, significantly reduce turn-around-times, and reduce inventory costs. MRP is not presently a part of the Depot Master Work Schedule planning process, because of difficulties in forecasting annual rebuild requirements. Currently, replacement part requirements are not determined until the equipment item arrives at the depot and is inspected. Not-in-stock requirements have to be requisitioned, which contributes to logistic and administrative delay time in the depot maintenance cycle.

Timely forecasting for budget planning is essential to develop the Depot Master Work Schedule and material requirements planning. This thesis provides a method for using existing historical maintenance data to identify a usage interval when an item is actually in its deterioration phase. It can be projected several years in advance with relative confidence; then used for aggregate budget planning. Further, it can be used to aid Material Requirements Planning (MRP) in the Master Work Schedule.

4. An Alternative Approach That Incorporates Reliability Theory

The methodology reviewed in the literature regarding useful life estimates can be categorized into either "pure" reliability analysis, or "pure" cost analysis. Perry (1973) combines reliability analysis with operational availability to determine a measure of "effectiveness" of a system. Decisions about system replacement can then be made on a basis of both cost and effectiveness over time. Perry's model assumes a constant failure distribution for mobility items. Crow (1975) argues, as does

most of the reliability literature (e.g. Ascher and Feingold (1984)), that complex repairable systems such as vehicles experience deterioration with system age, and that after a certain point they become too unreliable to continue in service without undergoing rebuild or replacement. The model presented in this thesis seeks to incorporate reliability theory with maintenance cost analysis in order to determine a usage interval where a decision should be made about when to rebuild or replace a system. Using a combination of cost effectiveness and operational availability provides an alternate basis for decision making.

5. Validate Other Models

The use of reliability analysis can be used to validate conclusions drawn from other sources that are used for major program decisions. For example, the US Marine Corps is currently involved with several extended service life programs for ground combat equipment systems (HQMC, 1994). The ESP program performance can be evaluated after a sufficient amount of time has elapsed (and sufficient data is collected) using the techniques addressed in this thesis. The program's projected life extension can be compared to the actual equipment failure patterns after rebuild, which are used to estimate future failure patterns. In other words, the technique to be presented provides a way to quantitatively measure the effectiveness of the ESP. Lastly, this thesis provides a way to refine the linear cost versus age assumption in models such as the US Army TACOM's Tactical Wheeled Vehicle Useful Life Determination Program. The model developed here would allow TACOM to more accurately predict costs during the deterioration phase of equipment when failure costs are not linear.

D. SCOPE, ASSUMPTIONS AND LIMITATIONS

1. Scope

The scope of this thesis entails an application of reliability theory for complex repairable mechanical systems. Analysis of historical maintenance data on existing equipment will lead to expected costs associated with the "do-nothing" (minimal repairs policy) alternative for decision making, and is used to project future mainenance costs associated with keeping the system "as is." Maintenance costs associated with new programs or post-overhaul/upgrades are not derived, as these are available through the appropriate program office. For the purposes of this thesis, these costs are

accepted as given, and used as the alternative to doing nothing. The case analysis studies the M998 High Mobility Multipurpose Wheeled Vehicle (1¼ ton truck), which is an equipment item common to all types of Marine Corps units. The end result is to provide a means for predicting future maintenance costs based on an expected number of critical system failures during specified intervals. These failures can then be converted to costs, either in terms of replacement parts, direct-labor and overhead, or in terms of the downtime (operational un-availability). As such, other costs such as research, design, test and production are considered to be sunk costs and are not included.

2. Assumptions

The underlying implication of declining DoD budgets is that the Marine Corps will most likely be keeping its existing equipment for longer than the programs were originally planned for. The periods following the Korean and Vietnamese wars saw reductions in defense spending (Schick, 1990), where weapons and equipment systems remained in the defense inventory well beyond their useful or "book" life. Common examples are the Vietnam vintage CH-46 Medium Lift Helicopter, which has been in service for over 30 years, and the M151 (¼ ton jeep), which was in service for over 15 years. The M151's "design life" was six years (TACOM TWVULDP, 1985).

The decision of whether to replace or overhaul depends on how much useful economic life remains in an existing system based on the age and condition of the system, and on the cost of buying new. Reprocurement costs for low quantities of replacements (due to loss, accidents or combat action) may be extremely high for low production runs. Therefore, periodic overhaul may be the desired solution.

Other technical assumptions regarding general operation of the system and mathematical models are discussed in the applicable sections of this thesis. In general this thesis assumes:

- That the analysis of a "complex repairable mechanical system."
- The system is sufficiently complex such that no individual component or subsystem is the dominant cause of system failure. A Pareto analysis of part failures is used to support this assumption.
- Critical components are independent and serially connected, such that failure of any critical component causes a system operational mission failure.

- The reliability of the entire system is not significantly improved by a minimal repair, i.e., replacement of a single part (Crow, 1975).
- That overhaul/rebuild restores the stem to "same as new" or ready for issue condition with a reliability function nearly the same as a new system/replacement. The U.S. Army TACOM uses an 80% factor to estimate the effects of overhaul. That is, overhaul will increase the life of an item by 80% of the original economic useful life of an item.
- Repairs are not necessarily instantaneous, but the majority of the "downtime" is due to administrative or logistics delay time.
- The systems are in continual usage. Further, to predict future costs, annual mileage is simulated using the Monte Carlo technique, based on the distribution of available usage data. Since future mileages can not be known, average annual usage for like systems, organizations or geographical locations is used to predict future failures.
- Mean active maintenance time and mean corrective maintenance times are constant for given tasks, and will generally be the same for any program alternative.
- The effects of Product Improvement Programs, major system modifications or "Block Upgrades" are not considered in the analysis, since data is not specifically kept on "before" and "after" effects of overhaul for ground combat systems.
- The analyst interpreting the data results is experienced with the MIMMS database and general statistical concepts.

3. Limitations

Conclusions drawn from the techniques involved in this thesis are limited to the quality of the field maintenance data. In this case, data from the Marine Corps Integrated Maintenance Management System (MIMMS) database is used for the analysis. MIMMS is subject to data inconsistencies due to lack of training or supervision of input clerks at the field units. Techniques are used to eliminate bad data and improve the confidence of the analysis. Data was also available from the TACOM Sample Data Collection (SDC) in support of the Tactical Wheeled Vehicle Useful Life Determination Program, but was not used for the complete analysis since failure times were not available.

Secondly, care must be taken regarding the mathematical assumptions presented in the model. Probabilistic modeling presented in the next chapters is based on highly simplified assumptions. "Real world" factors must be taken into consideration when interpreting the results of the trend data. Ascher and Feingold (1984) present several important considerations for using reliability models.

E. ORGANIZATION OF THE THESIS

The thesis is organized into six chapters. Chapter II introduces reliability theory and outlines the methodology for determining the Rate of Occurrence of Failures for a series of failure points. It further describes the LaPlace Test statistic which indicates decreasing, constant, or increasing trends in the time between failure data. Chapter III discusses the MIMMS database, and outlines the steps for setting up the raw data for statistical analysis. The output data can be manipulated using a spreadsheet package, such as Microsoft Excel on a personal computer. Chapter IV is an explanation of the model, using the functional form of the time variant ROCOF presented in Sadlon (1993) and Crow (1975). Chapter V is a case application of the model given sample data on the M998 HMMWV. Chapter VI provides conclusions and recommendations.

II. RELIABILITY OF REPAIRABLE SYSTEMS

A. BACKGROUND

This chapter outlines repairable system reliability concepts, and provides some of the probability models and relationships used to describe system failure processes. By projecting expected future system failures, cost streams associated with the failures can be computed and used to make decisions about maintenance policies. Mathematical derivations are not provided in this chapter, rather, the final resulting models or formulas to be used for the analysis are presented. Sources of the models are provided if further clarification of the proofs or derivations are required.

In reliability theory, the concept of a *part* is different from that of a repairable system. It is important to begin by distinguishing the two concepts. The basic difference is that a part can only fail once, but a repairable system can fail many times (Ascher and Feingold, 1984). Therefore, the assumptions and mathematical models used to describe system failures are somewhat different from those used to describe failures of parts (which include non-repairable components and subassemblies). Although the models for system failures are more complicated than for part failures, the system failure process can basically be modeled according to the arrival pattern of the failure incidents, assuming a sufficiently complex repairable system. The failure pattern is generally described by the number of failures in a specified interval, and the duration between failures in the interval.

The main concept used to describe the failure patterns is called the "Rate of Occurrence of Failures," (ROCOF) denoted as $\rho(t)$. It is a time variant rate used to describe the reliability phases of the system life-cycle. The ROCOF is also described as the failure intensity, *force of mortality* (for non-repairable components), or *peril rate* (when describing repairable systems) in the literature. Maximum likelihood estimators, confidence bounds and hypothesis tests are provided which are used to estimate the ROCOF for repairable systems. Given the ROCOF, an expected number of failures can be forecasted for a specified future interval of time or usage. This function is used to make maintenance policy decisions based on failure costs in terms of dollars and/or readiness. Finally, the estimated parameters of the ROCOF can be used in models that gives the "optimal" expected useful life, and one that yields the optimal point in a system life-

cycle where the tradeoff between the cost of maintenance ("minimal repairs") and overhaul costs are minimized (Barlow and Proschan, 1965, and Dhillon, 1988).

B. TERMINOLOGY AND DEFINITIONS

This section defines the terminology to be used throughout this paper. Definitions and parameters vary throughout the literature which makes the research in some cases confusing. The primary sources used for the reliability parameters in this paper are drawn from Ascher and Feingold (1984), and Sadlon (1993). Other major sources include Barlow and Proschan (1965), Tobias and Trindale (1986), Dhillon (1988), and Crow (1975), however the latter four texts use some different terms, definitions, and notations for parameters. For consistency, Ascher and Feingold's (1984) terminologies and notations are primarily used.

1. Complex Repairable System

A complex repairable system consists of a large number of independently acting components, which, after failure to perform at least one of its required functions can be restored to performing all of its required functions by any method, other than replacement of the entire system (Ascher and Feingold, 1984). This thesis also distinguishes between "critical" components and non-critical components in the analysis of the actual data presented in Chapter V. Failure of a critical component results in the system not being able to perform its combat operational mission (however, failure of non-critical components will contribute to total maintenance costs). Crow (1975) states that if the system is sufficiently complex, consisting of many components, that replacing a single component may not decrease the system failure probability significantly. For example, replacement of a starter would not alter the probability of brake failure immediately after the starter's replacement. Crow further states that the nonhomogeneous model assumes idealistically that the system reliability (specifically the ROCOF) does not change at all after "minimal repairs."

2. Overhaul/ Rebuild and IROAN Policies

The Marine Corps defines the term *rebuild* as:

> ...that maintenance technique used to restore an item to a standard as near as possible to original or new condition in appearance, performance and life expectancy. This is accomplished through a maintenance technique or complete disassembly of the item, inspection of all parts or components, repairs or

> replacement of worn or unserviceable elements using original manufacturing tolerances and/or specifications and subsequent reassembly of the items.

(Marine Corps Order P4790.2,1994). For the purposes of this thesis, the terms overhaul and rebuild are used interchangeably. Due to fiscal constraints in the past several years, depot level rebuild programs have not been available for most ground combat systems. Rather, a concept known as "Inspect and Repair Only As Necessary" (IROAN) is being employed (Boak, 1988). The same directive defines IROAN as:

> ...that maintenance technique which determines the minimum repairs necessary to restore equipment, components or assemblies to prescribes maintenance serviceability standards by utilizing all available diagnostic equipment and test procedures in order to minimize disassembly and parts replacement.

Decision makers should be aware that overhaul does not guarantee the item will have necessarily the same reliability as a newly manufactured item. Ascher and Feingold (1984) uses the term "same as new" to mean that the overhauled system's reliability does not imply the original system reliability. For example, a high failure intensity for a brand new system may be observed during burn-in or debugging. In that case, he calls the condition "bad as new." Further, Lee, Puzzuoli and Hoogterp (1976) use simulation to show the effects of both the degree and time of overhaul on U.S. Army tactical wheeled vehicles. They conclude that when a vehicle is overhauled, meaning components with less than 60% of their life remaining were replaced, that the item was returned to about 90% of its original reliability (based on reliability when the system was brand new), not counting the effects of burn-in. As stated in Chapter I, the Army generally uses a factor of 80% of the original useful life to be the estimated life-extension after overhaul/rebuild.

3. Reliability

Blanchard (1992) defines reliability as

> ...the probability that a system or product will perform in a satisfactory manner for a given period of time when used under specified operating conditions.

Mathematically, reliability is expressed as the probability that an item will not fail during a specified interval, or

$$R(t) = 1 - F(t) \tag{2-1}$$

where F(t) is the cumulative probability function providing probability that an item will fail by time t. Ascher and Feingold (1984) emphasize that the models for part and system reliability analysis are different, and that the failure processes for parts and systems cannot be interchanged. The basic difference is that a system can fail many times, and be restored with minimal repairs, while a part can only fail once.

4. Failure and "Failure Rate"

A failure is an event that renders a system incapable of performing any of its functions is a satisfactory manner. The failure rate, normally expressed as λ, is the rate at which failures occur in a specified interval (Blanchard, 1992). The period between failure arrivals is typically called the "Mean Time Between Failures" (MTBF). MTBF is a suitable measure when the system failure intensity is constant. In this case, failures are described as independent, identically exponentially distributed random variables, characterized by the homogeneous Poisson process. However, the reliability literature (Barlow and Proschan (1967), Crow (1975), Ascher and Feingold (1984), Dhillon (1988) and Sadlon (1993)) shows that failure rates may decrease, remain constant or increase with time. A more appropriate measure for system reliability is described by Ascher and Feingold (1984), which is a time derivative of the expected number of failures over an interval. They refer to the ROCOF as the probability that a failure, not necessarily the first, occurs in an interval (0, t). The ROCOF is denoted as $\rho(t)$. If $V(t) = E[N(t + dt) - N(t)]$, where $[N(t)]$ is the number of failures occurring in (0, t), then let $\rho(t) = dV(t)/dt$. The ROCOF is generally recognized as the process that describes the typical system "bathtub curve" shown in Figure 2.1.

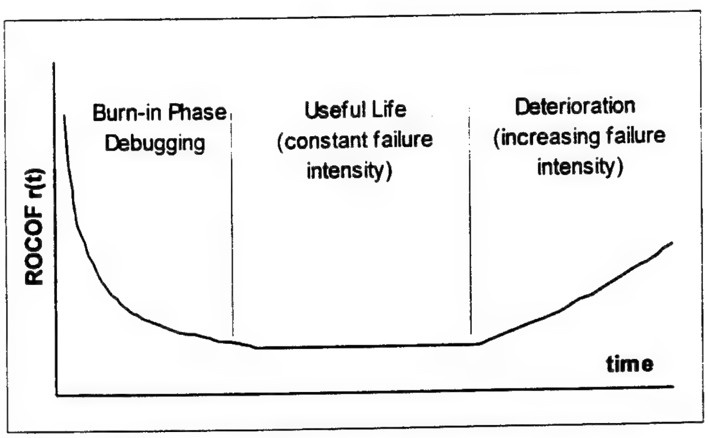

Figure 2.1 Repairable System Bathtub Curve

The literature on systems reliability normally uses the Weibull probability distribution to characterize system failures the failure intensity during the burn-in and the deterioration phases. Ascher and Feingold (1984), Dhillon (1988), Tobias and Trindale (1986), and Sadlon (1993) all, describe the time variant ROCOF for a nonhomogeneous Poisson process (NHPP) in the form:

$$\rho(t) = \lambda\beta t^{\beta-1} \tag{2-2}$$

The NHPP is described in Section 6.b. to follow. Note the special case when $\rho(t)$ is constant, then the parameter λ is the ROCOF of the homogeneous Poisson process, and the simple reliability function $R(t) = e^{-\lambda t}$ is used to calculate probabilities of mission success (Ascher and Feingold, 1984). Equation (2-2) provides the basis for the specific ROCOF function derived from the Weibull distribution which is introduced in the next section.

5. Weibull Distribution

Throughout the literature, the Weibull distribution is commonly used to model the reliability of complex repairable systems (Tobias and Trindale, 1986; Sadlon, 1993). The Weibull distribution is assumed to be an appropriate model for reliability of mechanical ground combat systems discussed in this thesis. It can model the burn-in, useful life, and deterioration phases of repairable systems. The Weibull distribution is a two-parameter, more generalized form of the exponential distribution, which is used in reliability models to describe the duration between failure events (Weibull, 1951). The Weibull distribution allows for a change of failure intensity over time. Depending on the shape/slope parameter (β), the Weibull distribution characterizes other failure distributions such as the Gamma, Raleigh, Extreme Value, or Normal distributions. This makes it a versatile function that can represent a family of various distributions. Table 2.1 summarizes special cases of the Weibull distribution for various values of the shape parameter (β).

Shape Parameter Value	Corresponding PDF	ROCOF Description
$0 < \beta < 1$	Gamma	Exponentially decreasing from ∞
$\beta = 1$	Exponential	Constant
$\beta = 1.5$	Log-normal (approx)	Rises to peak and then decreases
$\beta = 2$	Raleigh	Linearly increasing
$3 < \beta < 4$	Normal (approx)	Rapidly increasing
$\beta > 10$	Similar to Type I extreme value	Very rapidly increasing

Table 2.1 Weibull Probability Distribution Properties

For systems reliability modeling the two-parameter Weibull distribution is used, since it is reasonable to assume that the lower bound on system life is zero.[2] The probability density function of the Weibull distribution is defined as:

$$f(t) = \lambda\beta t^{\beta-1}\, e^{-\lambda t^{\beta}} \tag{2-3}$$

for $t \geq 0$, and $f(t) = 0$ elsewhere.

The Weibull cumulative probability distribution function is:

$$F(t) = 1 - e^{-\lambda t^{\beta}} \tag{2-4}$$

[2]The three-parameter Weibull would include a "location parameter" which is the expected minimum value of the random variable. In life-cycle reliability modeling, the minimum value is logically defined as zero, i.e., the minimum life of a system.

The probability of failure in the next instant of time, over the interval (t, t + dt) given the item has survived to t is called the hazard rate (for repairable systems, Ascher and Feingold call it the *peril rate*). The hazard or *peril rate* is expressed as:

$$\rho(t) = \frac{f(t)}{1 - F(t)} \tag{2-5}$$

If f(t) is the Weibull probability density function, then equation (2-5) yields the ROCOF:

$$\rho(t) = \lambda\beta t^{\beta-1} \tag{2-6}$$

The ROCOF is used to model the failure intensity of repairable systems. Equation (2-6) also provides the basis for predicting the expected number of failure to time t.

6. Point Process Models

The ability to measure and predict a system's reliability can be described by the pattern of failures. This section describes two types of point processes that can be used to model a systems failure process. The failure process, depicted in Figure 2.2, is characterized by point events occurring in a continuum such as operating time, or mileage in the case of vehicles (Sadlon, 1993). A point process is further defined by the failure event and the observed intervals between successive events.

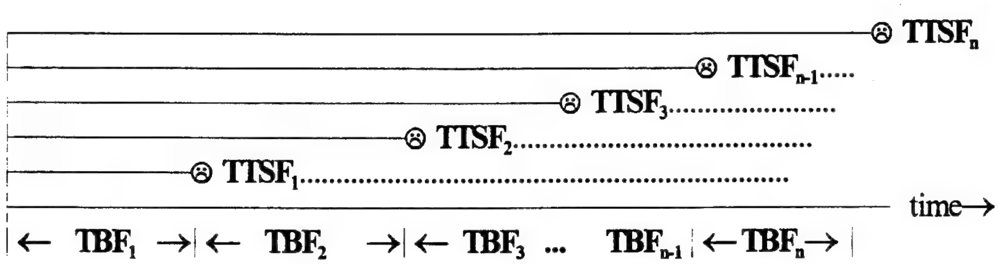

Figure 2.2 Repairable System Failure process

The system failure events are denoted by the (⊗) symbol. The total time to the i-th system failures (for $i = 1, 2, 3...n$) is denoted as $TTSF_i$, and the time between the i-th failure and the $(i + 1)$st failure is defined as TBF_i. The last occurrence of a system failure is denoted as $TTSF_n$. The $TTSF_i$s are obtained by forming the cumulative sums of the interarrival times. In the case of the MIMMS database, the TTSF is simply the meter reading at failure[3].

Generally, the number of independent observations occurring within an interval are described by the Poisson distribution with parameter μ, (denoted with subscript to distinguish it from the constant of the Weibul intensity function) while the durations between the intervals are described by independent exponential variables with parameter μ. This notion implies that the average number of failures per unit time interval is μ, and the mean duration between successive intervals is $1/\mu$ (Neter, Wasserman, Whitmore, 1993). Note that, as stated in the previous section, use of the two-parameter Weibull distribution allows for μ to vary with time. Knowing the TTSF's, a point process can be modeled to describe the failure patterns. This thesis is concerned specifically with the HPP and NHPP point process models.

a. *Homogeneous Poisson Process*

The homogeneous Poisson process can be used to model a system whose failures are independent and identically exponentially distributed, and which show no tendency to increase or decrease. A mechanical system which is in its "useful life" or "normal" phase usually show an HPP failure characteristic, as failures occur randomly. Crow (1975) points out however, that many complex mechanical repairable systems, such as vehicles, tanks, or fork-lifts, generally experience a deterioration phase and may seldom achieve the equilibrium state of a homogeneous Poisson process (HPP).

b. *Nonhomogeneous Poisson Process (NHPP)*

The NHPP differs from the HPP in that the ROCOF ($\rho(t)$) varies with time rather than being constant, implying that the failure times are not necessarily identically distributed (Ascher and Feingold, 1984). They further show that the expected number of failures V(t) in any interval $(t, t + dt)$ is given as:

[3]The assumption is that the mileage on the Equipment Repair Order (ERO) close date is very close to the mileage at failure, even though in reality this would not normally be the case. Chapter III details the assumptions about the MIMMS database.

$$V(t) = E[N(t+dt) - N(t)] = \int_t^{t+dt} \rho(t)dt \tag{2-7}$$

Substituting equation (2-6), the functional form of the time variant of the ROCOF, $\rho(t)$, into equation (2-7), the expected number of failures during an interval can be evaluated as a definite integral:

$$V(t) = \lambda t^{\beta} \Big|_t^{t+dt} \tag{2-8}$$

Equation (2-8) is the primary interest for developing the future life-cycle maintenance cost model used in this thesis. Equation (2-8) yields the expected number of failures in the interval (t, t+dt) hours (or miles) for the system. This equation can be evaluated over specified intervals, and multiplied by expected costs associated with failures in order to derive maintenance policies.

C. TREND ANALYSIS

There are several methods for determining whether a system shows improving, constant, or deteriorating trends in the time between failures. Trend analysis is useful in that it provides a "snapshot" of where the system is in its life-cycle, and the degree to which the peril rate of the system is changing. Trend analysis also provides the basis for classifying a data series as HPP or NHPP. Ascher and Feingold (1984) provides several methods for trend testing, namely: 1) graphical plotting techniques, 2) test statistics, and 3) the MIL-HDBK-189 (1981) test. Graphical plotting and the LaPlace trend test statistic described by Ascher and Feingold (1984) are used for this analysis.

1. Graphical Plotting

Graphical plotting is useful as a visual check of the condition of a system's failure profile. Constructing a graphical plot of cumulative operating time against the cumulative number of failures illustrates the difference in deteriorating or improving trends. A plot concave down with respect to the origin indicates an improving system, due to increasing spacing between the system failure events. Conversely, a plot convex (up) with respect to the origin indicates a deteriorating system. The graph shown in figure 2.3 illustrates the relationship between the expected number of cumulative failures and operating time, for values of $\beta = 1$, > 1 and < 1. The curves illustrate

the three possible life-cycle phases described by the bathtub curve, and are useful when interpreting failure plots and trends over different intervals in the system's life.

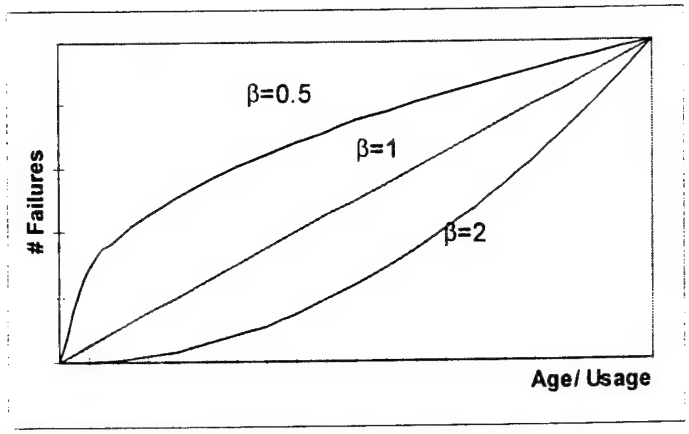

Figure 2.3 Expected Number of Failures over Time for Various Values of β

2. LaPlace Test Statistic

The primary indicator used in this thesis to determine whether a system is improving, in a steady state, or deteriorating is through the use of the LaPlace test statistic. The LaPlace test statistic indicates trends in the successive interarrival time data. The LaPlace test statistic for individual systems can be computed directly from existing MIMMS-AIS historical data. Further discussion on the actual data is presented in Chapter V.

To calculate the test statistic (U), a system is operated until a prespecified number of failures have occurred, or up until a specified time. Data in the first case is called *failure truncated* data, the latter case is called *time truncated* data (Crow, 1975). The interarrival times (TBF_i) are observed, based on the start time of the data interval. Recall that the $TTSF_i$s are the observed failure times measured from the origin. Let $TTSF_n$ denote the *n-th* observed failure time in the interval. Sadlon (1993) gives the LaPlace test statistic for a process with "*n*" failures as:

$$U = \frac{\left[\left(\sum_{i=1}^{n-1} TTSF_i\right)/(n-1)\right] - \left(\frac{TTSF_n}{2}\right)}{TTSF_n\sqrt{1/(12(n-1))}} \qquad (2\text{-}9)$$

The conclusions drawn from the test are:

- U approximately equal to zero indicates lack of trend. Assume HPP.
- U > 0 indicates that interarrival time trends (TBF_i) are decreasing, indicating system deterioration.
- U < 0 indicates that interarrival time trends (TBF_i) are decreasing, indicating system improvement, or reliability growth (such as debugging or "burn-in").

After system failure data have been collected and trend tests conducted, maintenance policies based on the condition of the equipment can be determined. For example, if the number of system failures is relatively constant (suggesting $U \cong 0$ and HPP failures), and that sufficient program dollars have been allocated for "routine" operations and maintenance, then the status quo maintenance policies are usually acceptable. However, as the number of system failures over the intervals increase with age, then overhaul or replacement may be considered more desirable alternatives. The status quo maintenance policy (performing minimal repairs each time the system fails) will generally have linear cumulative annual costs during the *useful life* of the system. However, as the system begins to deteriorate, the costs can increase linearly or exponentially with time depending on the failure intensity, or ROCOF. The value of the LaPlace test statistic can be used to interpret how rapidly the system is deteriorating. As the value of U increases, the slope of the ROCOF increases, indicating that the system is deteriorating rapidly.

The next section describes the Maximum Likelihood Estimators (MLEs) used to determine the shape or *slope* parameter β, and the scale or characteristic life parameter λ for the failure process model described in equation (2-6). Before the estimate V(t) can be applied to policy decisions, the values for the parameters λ and β must be estimated.

D. MAXIMUM LIKELIHOOD ESTIMATORS FOR λ AND β

The LaPlace trend test statistic indicates the trend in the times between failures for a system. If the results of the test conclude that a system is deteriorating (U > 0), then the NHPP failure process is assumed. Assuming an NHPP, and the Weibull failure intensity described by

equation (2-6), then by observing the failure events of a system, Crow (1975), and Bain (1978) derive MLEs for λ and β. These MLEs can be estimated from data existing in the MIMMS-AIS database which contains the maintenance history data on Marine Corps ground combat equipment. The times to system failures or, the meter readings at each *i*-th failure are used to calculate the MLEs. Assuming that the failure observations starting from system time zero, the maximum likelihood estimates for K=1 system are (Sadlon, 1993):

$$\beta = \frac{n}{\sum_{i=1}^{n-1} \ln \frac{TTSF_n}{TTSF_i}} \tag{2-10}$$

and,

$$\hat{\lambda} = \frac{n}{TTSF_n^{\beta}} \tag{2-11}$$

where, $TTSF_n$ = Total time to last observed system failure

$TTSF_i$ = Total times to i-th system failures (see figure 2.2)

n = Total number of system failure observations

Crow (1975) also provides the conditional MLE β for q = 1,2,3,...K systems:

$$\beta = \frac{\sum_{q=1}^{K} M_q}{\sum_{q=1}^{K} \sum_{i=1}^{M_q} \ln\left(\frac{TTSF_{n_q}}{TTSF_{i_q}}\right)} \tag{2-12}$$

where: $TTSF_n$ = Total Time to *n-th* System Failure of the q-th system

$TTSF_{i_q}$ = Total Time to *i-th* System Failure of the q-th system

and, N_q = Number of failure observations for the q-th system

$$M_q = \begin{cases} N_{q-1} & \text{for failure truncated data} \\ N_q & \text{for time truncated data} \end{cases}$$

also,

$$\hat{\lambda} = \frac{\sum_{q=1}^{K} M_q}{\sum_{q=1}^{K} TTSF_{i_q}^{\beta}} \tag{2-13}$$

Maintenance or failure data is most likely not available on most Marine Corps systems dating back to their fielding date, i.e., when the system was brand-new ($T_0 = 0$), therefore, the MLEs for β and λ must be computed by rescaling the $TTSF_i$s. The timeline below illustrates the situation where only a portion of the system's history data is available:

Time=0 → *Present*

← data unavailable → ← past 36 months of data →

$TTSF_1$ $TTSF_2$ ... $TTSF_n$

↑

Observed failure events

For example, suppose failure data is available for the period 22,000 miles to 60,000 miles for a vehicle. Equations (2-10) through (2-13) assume that the $TTSF_i$s are observed since T_0= 0. Therefore, the known data must be rescaled to reflect the first observed failure as time zero. The implication is that the first failure observation in the data set will become zero, and the subsequent failure times reflect the differences between the next failure arrival times. To illustrate, consider the data below:

Known Failure Mileages	*Rescaled* Failure Mileages
22136	0
24758	2622
28734	3976
33489	4755

The actual MIMMS-AIS $TTSF_i$ data used for the case analysis of the HMMWV sample population required rescaling. Rescaling the $TTSF_i$ data is only necessary when failure data for the entire life history is unavailable. Note that the resulting parameters β and λ, and the LaPlace statistic describe the ROCOF for the *actual* data interval, i.e., for the interval 22136 to 33489 miles in the example above. Due to the cost and lack of need for maintaining archive maintenance data, MIMMS-AIS history data only contains the past 36-54 months of a system's maintenance history. Since the objective of this analysis is to estimate the present failure intensity in order to forecast the remaining life of the system, the past 36-54 months of historical data is most likely acceptable, given that there are enough data points to arrive at a confident conclusion.

1. Confidence Intervals for β and λ

Decision makers using the model presented in this thesis should be aware of the confidence interval associated with the point estimators described in the preceding section. As Chapter III will show, considerable historical data exists for Marine Corps principal end items through the MIMMS-AIS database. Generally, given more observations, and longer total observed times for the samples, better conclusions can be drawn about the overall status of the equipment. The purpose of this section is to provide the confidence intervals discussed by Crow (1975) which are used to evaluate the confidence intervals around the point estimators.

The chi-squared statistic is used to test hypothesis about the true value of β using the fact that $2M\beta/\beta$ is distributed as a chi-square random variable with 2M degrees of freedom. Thus, the 100(1- α)% lower and upper confidence limits (LCL, UCL respectively) for β using the χ^2 statistic are:

$$\beta_{lb} = \beta\frac{\chi^2(\frac{\alpha}{2}, 2M)}{2M} \qquad \text{(LCL)} \qquad (2\text{-}14)$$

and

$$\beta_{ub} = \beta\frac{\chi^2(1-\frac{\alpha}{2}, 2M)}{2M} \qquad \text{(UCL)} \qquad (2\text{-}15)$$

where $\chi^2(\alpha, 2M)$ is a chi-squared statistic with (1-α) quantile and 2M degrees of freedom.

After an estimator for β has been calculated, Crow uses the result together with the failure arrival times to estimate confidence intervals for λ. Under time truncated testing on K systems, the lower and upper confidence bounds respectively, for λ are:

$$\lambda_{lb}(\beta) = \frac{\chi^2(\frac{\gamma}{2}, 2N)}{2\sum_{q=1}^{K} TTSF_q^{\beta}} \qquad \text{(LCL)} \qquad (2\text{-}16)$$

$$\lambda_{ub}(\beta) = \frac{\chi^2(1-\frac{\gamma}{2}, 2N+2)}{2\sum_{q=1}^{K} TTSF_q^{\beta}} \qquad \text{(UCL)} \qquad (2\text{-}17)$$

These equations are provided as reference for the case analysis of the Marine Corps data presented in Chapter V.

E. OPTIMUM REPLACEMENT/OVERHAUL TIME WHICH MINIMIZES EXPECTED MAINTENANCE COSTS

Barlow and Proschan (1965) discuss a model to find an optimal interval for system replacement or overhaul that minimizes the expected costs of performing minimal repairs. For a deteriorating complex system, they assume that minimal repairs (such as replacing a glow plug) do not disturb the system's ROCOF. Therefore, at some point, reliability and operational availability become unacceptable due to decreasing times between failures. This is consistent with the assumptions made in Chapter I. Here, it is assumed that overhaul or replacement renews the system to an "same as new" level of reliability, to the extent that operational availability meets expected mission standards. They refer to work by Barlow and Hunter (1960) to calculate the optimal period between overhaul or replacements for systems over an *infinite* time span. Barlow and Proschan (1965) show that when a system has a Weibull intensity function, with $\beta > 1$ (system is deteriorating), that the time which minimizes the expected maintenance cost is given as:

$$T^{*} = \left[\frac{c_2}{\lambda(\beta-1)c_1}\right]^{1/\beta} \tag{2-18}$$

where, c_1 = expected cost of minimal repairs
c_2 = cost of system replacement or overhaul

More discussion of equation (2-18) is presented in Chapter IV as well as cash flow analysis of maintenance policy and overhaul alternatives.

Dhillon (1988) offers a simple model to estimate the economic useful life L_e of a repairable system expressed as:

$$L_e = \left[\frac{2(K-S)}{C}\right]^{\frac{1}{2}} \tag{2-19}$$

where C is the annual increase in maintenance costs, K is the acquisition cost of the system, and S is the salvage value.

Both equations (2-18) and (2-19) can be used as rough estimates to the numbers derived through the program managers, but should not be used exclusively for the ultimate decision. They

can be helpful for determining how close some of the useful life estimates and overhaul intervals are based on known costs.

F. SUMMARY

The purpose of this chapter is to introduce the basic reliability theory and models associated with complex repairable systems. The goal is to determine the projected ROCOF for a system based on historical data. System reliability is essentially an analysis of the arrival patterns of system failures. Knowing the failure arrival patterns, the data can be fit to a likely distribution to forecast future system failures. The hazard, or peril rate under the Weibull distribution can be used to represent the system ROCOF for each stage of its life-cycle. The LaPlace test statistic shows whether system failure trends are improving (burn-in), constant (normal life), or deteriorating. When the LaPlace statistic indicates that the system is deteriorating, the NHPP assumption is used to model the failure process. Maximum likelihood estimators for the ROCOF parameters are derived from the system data, and confidence intervals can be constructed around those estimators. Knowing the parameters of the ROCOF, cost-minimizing equations can be used to determine an optimal interval for system overhaul or replacement. The next chapter describes the Marine Corps maintenance database that is used for the case analysis.

III. MIMMS-AIS DATABASE ANALYSIS

A. BACKGROUND

The purpose of this chapter is to describe the data available for use with the formulas discussed in Chapter II. The Marine Corps Integrated Maintenance Management System-Automated Information System, Field Maintenance Subsystem (MIMMS-AIS FMSS) is supported by a centralized database which contains historical maintenance information on Marine Corps ground equipment. MIMMS-AIS is used to record, process, store, and produce required maintenance management data for use at all levels of command in the Marine Corps. Daily shop actions and equipment job status are manually entered into the FMSS by Fleet Marine Force organizational and intermediate level maintenance shops. Daily, weekly, monthly or as-required output reports are generated by the FMSS for use at all management levels. A key feature is the ability to provide information required to support maintenance engineering, resource management, and maintenance production. MIMMS-AIS interfaces with the Marine Corps supply system (SASSY) which provides for all data pertinent to requisitioning, status, issue, and cancellation of repair parts (UM 4790-5, 1987).

Another data source for equipment common to the USMC and U.S. Army, (such as tactical wheeled vehicles) is through TACOM. TACOM tracks specific principal end items throughout their life-cycle, and monitors the repair shops where the items are maintained, which gives it a level of control over the quality of the data in the sample data collection (SDC). Marine Corps decision makers should consider any operational usage differences between Marine Corps and Army systems when using TACOM's SDC. In most cases, it can be assumed that usage of common principal end-items for both services are the same.

Although this chapter describes procedures to analyze the MIMMS-AIS data, it is intended to apply also to the next generation maintenance management system, the Asset Tracking Logistics and Supply System II (ATLASS II). The general concepts and approach discussed here are assumed to be valid for both systems.

B. SHOP MAINTENANCE PROCEDURES AND ERO TRANSACTION FLOW

This section briefly describes the procedures used at the maintenance shop level, including the flow of transactions, in order to understand how to interpret the data and identify inconsistencies. The Equipment Repair Order (ERO) is an administrative form (NAVMC 10245),

identified by a unique number, used to track the maintenance progress of a single end-item (repairable system) in the maintenance cycle (TM 4700-15/1, 1994). It is the source document for all maintenance related activities, including calibration, modification, and scheduled maintenance. EROs are initiated for any corrective or scheduled preventative maintenance performed at second echelon or higher repair levels (MCO P4790.2, 1994). Data input fields on the ERO and subsequent status changes are used to generate the various maintenance management automated reports. In the "real world," the reliability of the input data is subject to the level of training and supervision of the input clerks; therefore, an understanding of where the data comes from is necessary.

The ERO includes data such as the date received in shop, serial number, item nomenclature, defect(s), maintenance category and other descriptive maintenance data. Input codes for each ERO field are provided in UM 4790-5. Daily, all new EROs and status changes to existing EROs are keypunched by data clerks into MIMMS-AIS, and transmitted to the Regional Automated Services Center (RASC) mainframe via local area network or other medium. ERO change transactions are submitted whenever the maintence category, defect description, repair status, receipt of parts, or other status changes occur. Repair parts, components, and secondary repairables can be requisitioned through MIMMS-AIS since it interfaces with the supply system during the daily update cycles. Replacement parts are requisitioned for the ERO using an "ERO Shopping List" (EROSL, NAVMC 10925). When all parts have been received and applied to the system, repairs are completed and quality control checks are done. If no further maintenance actions or repairs are required, the ERO is then closed. The final maintenance data pertaining to the ERO to include all received parts, the primary meter reading (mileage, hours, etc.), and direct-labor hours then become part of the ERO history for that item. These items are stored as database elements for each ERO record. In Excel, they are the column headings for the file, and each separate ERO is a row, or database record.

A flow diagram of general shop maintenance procedures is found in Appendix F of the MIMMS Field Procedures Manual (MCO P4790.2C, 1994).

1. Identification of Failures

System failures are identified one of two ways; either by the equipment operator during usage, or by the organizational maintenace shop during the performance of scheduled preventative maintenance (SPM). Detailed inspections of components and subassemblies are performed during

SPM's, and "worn out" or unserviceable components are identified. Normally, the equipment technical manual (TM) will specify serviceability standards for components. Although a part has not necessarily failed, if its condition is worse than the standards, it is replaced. For our purposes, this condition is defined as a part failure. If (unscheduled) corrective maintenance (CM) is identified during the conduct of a scheduled preventative maintenance ERO, then normally a separate CM ERO is initiated (TM 4700-15, 1994). The other method of failure identification is when the equipment operator identifies a system failure during system prechecks or operation. In that case, the defect is identified to the supporting maintenance shop and an ERO is initiated.

2. MIMMS-AIS History Files

The MIMMS-AIS Master ERO File contains approximately 36 past months worth of ERO history for all systems which had maintenance performed, recorded and input by unit maintenance shops. The data of interest for this analysis includes the time/mileage between EROs, the active maintenance time interval (time between the open and close dates of the ERO), labor hours, and parts applied under each ERO.

Historical maintenance data is captured on a quarterly basis by each of the RASCs and is transmitted to a central database at the Marine Corps Logistics Base, Albany, Georgia. The historical MIMMS-AIS data serves as the basis for determining parts usage and costs, labor hours, repair category and status, maintenance engineering, modification control, and other descriptive repair data. This data can also be converted into the chronological time-between-failure statistics discussed in Chapter II for analysis. Detailed discussion on the MIMMS-AIS FMSS can be found in MIMMS-AIS Users Manual (UM 4790-5, 1987).

C. "REAL WORLD" DATA INTERPRETATIONS

1. MIMMS-AIS Primary Meter Readings

In the current system, the meter reading (mileage) is recorded when the ERO is *closed*, not when the system is inducted into the shop for maintenance. The implication is that the system can, and normally is, operated during the period while the ERO is open. This means that the meter reading is not the Time-At-*Failure* but rather the Time-At-*Restoration*. Under ideal circumstances, (i.e., instantaneous repair) these would be equal, but in the "real world," they are not. For the model presented in this thesis, the assumption is that the relative difference between

the meter reading at failure (when the ERO is initiated) and when it is closed is not significant, in terms of the total life usage. That is, if the $TTSF_n$ is large relative to the intervals around the $TTSF_i$s, then we should not be concerned between the differences in meter readings[4].

Example: Suppose an M998 HMMWV had its i-th mission operational failure on January 1st with a mileage ($TTSF_i$) of 16,000 miles. It is inducted into the maintenance shop that day and an ERO is opened on the item. During the diagnostic inspection, several parts are identified as needing replacement; an alternator to restore the HMWWV to operational status, and several non-critical components. The same day, the alternator is exchanged for a rebuilt one at the Maintenance Float activity[5], and the vehicle is restored to a combat operational status. However, the non-critical parts are back-ordered in the supply system, and the ERO remains administratively open in a short-parts status. In the meanwhile, the HMMWV is used for a field training exercise and accrues mileage. The non-critical parts arrive on March 10th, and the HMMWV is recalled into the shop for the parts to be applied. The mileage of the vehicle when the ERO is closed is 16,875. The only meter reading that is visible in the MIMMS-AIS history associated with this particular ERO is 16,875.

The example above is not unlike what actually occurs in most Fleet Marine Force units. MIMMS-AIS currently does not capture the mileage at failure, so the TTSF data available for the analysis is based on the assumption that the difference between mileage at failure and mileage at restoration is small relative to the total system mileage. Recommended solutions to this problem are offered in the Conclusion chapter of this thesis.

Another significant problem with meter readings in FMF maintenance shops is inaccurate data input. For reasons due to lax shop management procedures or difficulties in getting the FMSS to "close" the EROs, often times the actual equipment meter readings are intentionally not correctly entered. The most common "shortcut" is to enter "999999" in the meter-reading field of the ERO to force the system to accept the ERO-close transaction. Other common meter

---

[4]the "true" $TTSF_i$ would be the mileage at restoration (ERO close) minus the mileage at the i-th failure. We assume for this thesis that the difference is insignificant compared to the total mileage at the most recent failure, $TTSF_n$.

[5]The Maintenance Float Activity Groups provide a pool of ready-for-issue secondary repairables (SDRs), either new or rebuilt, in exchange for unserviceable SDRs from customer units.

readings include low whole numbers such as 1, 10 or 100. A second observation is that sometimes the julian date of the close transaction is inadvertently entered in the meter-reading field. This situation is usually obvious when reviewing the data. For example, a mileage of "94032" miles entered on February 1st, 1994 (94032 julian date) is easy to spot. The third common problem is that some of the meter readings were entered with the tenths digit included, when MIMMS-AIS does not allow for tenths. In this situation, the meter-reading in the data should be screened for the following pattern:

ERO	Date	Meter Reading	Miles Between Failures (computed field)
PK345	3/15/93	16,235	
PK124	5/04/93	17,044	809 actual
PJ874	9/18/93	177,355*	160,311 (691 actual)
PM221	10/21/93	17,856	-159,499 (121 actual)

* In this example, it is obvious that the mechanic included the tenths reading from the odometer, when 17,735 miles should have been entered. A logic flag can be used to identify this condition, and the data can be manually adjusted if the mistake is obvious enough.

The last condition that creates "suspect" meter-reading data is when the physical meter itself is replaced. In this case, the logic flag might highlight a low mileage reading following a high mileage reading. This situation could also explain when the meter reading is a low number such as "1" or "10." In that case, a defect code would appear in the ERO history reflecting "METER-RPLC" in MIMMS-AIS, or code "X34." If the "X34" code does not appear in the defect-code field of the ERO history, then the analyst should assume that the meter reading is suspect input. For the data on the HMWWV's used in the case analysis, approximately twenty percent of the meter readings were "suspect" for reasons cited above, and were scrubbed prior to analysis.

2. Multiple EROs Open Simultaneously on the Same System

Multiple corrective maintenance EROs are allowed to be opened on an equipment system at one time, which sometimes creates a problem with ordering the MIMMS-AIS failure data. For example, an unscheduled CM ERO may be open in a pending status on an item that is later used in support of a separately funded exercise. Repairs incurred during the exercise have to be recorded under a separate CM ERO to reflect the different accounting data. At one time, two EROs can be open at the same time on the same item. There is no problem in the analysis if the first ERO is closed before the second. However, if the repairs for the second ERO are done

quickly (i.e., the parts were immediately available), the second ERO might be closed out before the first. Since the Master ERO History files are sorted by the date EROs are opened, the mileage will appear to have *decreased* for the second ERO, and would reflect a negative time-between-failures. For this reason, the raw MIMMS-AIS data should be either be resorted by the ERO *close dates*, or manually adjusted in order to have the mileage reflect sequential failures. The use of a logic flag, such as "IF [Miles Between Failures < 0]" will identify these situations. Approximately ten percent of the data used in the case analysis fell into this category. Appendix A provides the logic flags used to screen the Excel data.

3. Long Maintenance Cycle Times for EROs

A final issue to be considered when analyzing the raw MIMMS data is the fact that most EROs remain open for a considerable length of time, which means that the EROs can cover multiple separate failures with only one (final) meter reading recorded. The effects of EROs staying open for so long is that any meter readings for subsequent failures other than defect that warranted the ERO in the first place are not recorded. Unit level maintenance on organic equipment is often recorded on "perpetual EROs" for administrative convenience. The MIMMS-AIS data for the case analysis had a mean ERO time (the difference between the close and open dates) of 120 days. The mean lag time between when parts were ordered and when they were received was approximately 20 days. The long ERO times impacts the Total Time to System Failure (TTSF) data, in that much of it is not recorded in the system. Despite these problems, the instananeous repair assumption still applies in this thesis. It is assumed that critical repairs are completed the same day that parts are received, which is normally true for most Marine Corps maintenance shops.

Example: Suppose an M998 HMMWV is inducted to the shop on March 1st due to a bad starter. After inspection and acceptance, the starter is exchanged at the Maintenance Float Activity, but several other non-critical parts are backordered. The vehicle is restored to operational status the next day, while the ERO remains open pending receipt of the other parts. A few weeks and several hundred miles later, the HMWWV has another system failure due to a wheel seal. It comes into the shop again, and the wheel seal and several other parts are requisitioned under the *existing* ERO. The existing ERO is used for convenience since it is already open for that system's serial number. The cycle continues until all of the requisitioned

parts have been received and applied. It is not unusual for some EROs to remain open on individual equipment systems for over six months.

Unfortunately, MIMMS-AIS currently does not reflect mileages at subsequent failures under the same ERO. This concept may account for a portion of the variance which widens the confidence intervals in the data. Program managers, and other decision makers at the ILSD should keep in mind the factors that limit the data. In most cases it can be assumed that the parts are applied on the same day that they are received, so that the instantaneous repair assumption is valid, but it does not count down-time due to administrative or logistics delays.

One possible way to address this would be to measure the time between when "batches" of parts are received and when the next "batch" of parts are ordered for a system under the same ERO. Here, we define a the failure point as the date on which parts were requisitioned, assuming parts are requisitioned on the same day that the system failed. We further assume that critical parts are applied to the vehicle the same day they are received. The interval between when a batch of parts were received (and the system restored) and when the next batch was subsequently ordered (due to the next failure) would be the TBF_i. To convert to miles, multiply the interval in days/years by average daily/annual mileage. Unfortunately, the real world data has far too much variance in equipment usage to draw any meaningful conclusions. Using an indirect means to compute failure intervals is not desirable. Nevertheless, this alternative would be a better way to define the interarrival of failure times, given a system design change that incorporates miles at failures in the MIMMS-AIS system.

The sample data collection (SDC) used by TACOM does attempt to record the mileage at each maintenance incident. Further, cumulative miles are accounted for when meters are replaced. However, the TACOM data that was provided for this analysis only contained equipment mileages at the beginning and ending of the quarterly sample periods. The actual meter readings at the *i*-th failures were not available, therefore trend patterns in the system failure data was not visible, and therefore not conducive to this analysis.

D. PREPARATION OF THE RAW MIMMS-AIS DATA FOR USE WITH MICROSOFT EXCEL (SPREADSHEET)

Analysis of the MIMMS-AIS data utilized Microsoft Excel, a Windows-based spreadsheet for personal computers. The data is collected through standard procedures outlined in the MIMMS Field Procedures Manual (MCO P4790.2C, 1994), and the Users Manual (UM 4790-5,

1988) and downloaded via mainframe computer into database files. Sample sizes should be determined by standard statistical methods, however analysis of the raw data is limited to the memory capacity of the PC being used. System memory should be considered in addition to required sample sizes when using the methods presented in this thesis. After the data is obtained, it must be converted into a form that can be used for the analysis.

Appendix A contains a description of the database fields, formulas and logic flags used for the model. In general, each row of the MIMMS-AIS database constitutes a maintenance record, such as an ERO and associated parts requisitioned. Additional documentation can be obtained from the author.

1. Major Data Categories

The first step in the data preparation is to specify to the data source the sample size and the repairable system to be analyzed. MIMMS-AIS contains approximately the past thirty-six months of historical data on all repairable systems in the Marine Corps inventory. Equipment is designated by its model nomenclature, but more specifically by other descriptive codes or numbers such as the National-Stock-Number (NSN) or its Table of Authorized Material Control Number (TAMCN). The data query was based on a single TAMCN. Secondly, the ERO History file can be segregated by Regional Area Codes (RACs), such as U.S. East Coast, U.S. West Coast, and the Western Pacific region (Okinawa). Usage and failure patterns may be different for each of these populations, so the data was broken down by separate RAC for the analysis. Lastly, the year of manufacture, or other data such as lot number may contribute variation in the population's failure patterns. The TACOM SDC database includes the equipment manufacture year directly in the data. MIMMS-AIS however, does not contain the year of manufacture in the database. That data is available through the respective inventory managers at MCLB, Albany, and has to be merged separately with the MIMMS-AIS data.

The next step is to sort the data and purge database entries that show inconsistencies or are "suspect" as described earilier in Section C.

2. Sorting and Purging the Data

The data requested should be sorted by serial number, and then by the "date recieved in shop," which is assumed to be very close to the date of system failure. In certain cases it may be advantageous to sort by the ERO close date instead of the open date, due to the multiple ERO problem described earlier. To properly use the non-homogeneous Poisson process (NHPP)

assumption described in Chapter II, recall that the data must be chronologically ordered according to the sequence of *i*-th failures. It is assumed that regardless of whether the data is sorted by the open or close dates of the EROs, that the meter-readings at failure (restoration) are in the proper sequence.

Logic flags are used to highlight "suspect" or inconsistent data, such as the bad meter readings described in Section C. Logic flags are also used to identify the next ERO recorded on the same serial number, or to differentiate between different serial numbers. Use of numeric logic flags can be used to count the number of records that meet a specified criteria. These logic flags and counters are summarized in Appendix A. Suspect data such as the meter readings described earlier should be eliminated.

Non-critical parts ordered should not be counted as system operational mission failures. Critical components that do cause mission operational failure are identified in MIMMS-AIS by a "Combat Essentiality Code" (CEC) equal to 0, 1, 5, or 6. EROs not meeting this criteria should not be considered as mission operational failures. These are used as query criteria for the data extract.

A caution: MIMMS-AIS uses a field called a "category code" which defines whether an ERO is open for a mission operational failure or non-critical maintenance. *All* category codes must be requested in the query, since an ERO designated with a mission critical category code may be downgraded to non-critical repairs (Category code "X" or "N") prior to closing the ERO. Therefore, to query the system only for Category code "M" (system failure) EROs would cause missing data. It is better to define mission operational failure, (critical maintenance EROs) by the CEC codes of the parts requisitioned to restore the item.

3. Time Truncated and Failure Truncated Data

Chapter II provided two sets of maximum likelihood estimators presented by Crow (1975) for determining the ROCOF function for a system. The time truncated data holds the ending time for the observations constant and number of failures as variable. The failure truncated data observes systems to a specified number of failures, where the end time of the observations is variable. The MIMMS-AIS data readily lends itself to time truncation data. For example, a database criteria can be specified to provide all records for vehicles with less than or equal to 50,000 miles. Then, we simply count the number of failures and measure the intervals between

failures. Hence, for the case analysis presented in Chapter V, the data is time truncated and the appropriate formulas from Crow (1975) are used.

4. Julian Dates in MIMMS-AIS

MIMMS-AIS uses Julian dates to record maintenance actions. That is, January 1st, 1994 is 94005, and December 15th is 94349. In order to perform computations with these dates, they need to be converted to year and date values in Excel, and then combined with logic statements to correctly perform subtractions. For example, if we want to compare the difference in dates between when an ERO is opened and when it is closed, we cannot always perform the subtraction directly. Suppose an ERO was opened on December 15th, and closed on January 5th. The calendar difference is 21 days, however the difference between Julian numbers is 656. An algorithm for computing these differences is provided in Appendix A.

5. Pareto Analysis

In order to show that a repairable system is sufficiently complex enough to use the model presented in this thesis, it is useful to conduct a Pareto analysis of the system failure causes. Since the data identifies replacement components that presumably caused the system failures, the MIMMS-AIS data can be transformed into a Pareto ranking to draw conclusions about the primary contributors to system failure. The 80/20 rule might be used to validate the "sufficiently complex system" assumption. If less than 20% of the components cause 80% or more of the system failures, then either poor quality components or improper equipment operation might be the causes of the system failures, and further investigation would be needed prior to making an overhaul decision. Conversely, if greater than 20% of the components cause 80% of the system failures, then the system is assumed to be sufficiently complex to use the assumptions. Reasonable judgement should be used when components are used to define system failures; for example, tires, brake shoes, and batteries for vehicles are replaced on a regular basis due to normal wearout, and may not need to be considered when evaluating the system failure complexity.

Microsoft Excel makes the Pareto analysis relatively easy. The repair part data can be sorted by stock-number and counted. A *pivot table* was generated which provides usage subtotals for each separate component. The relative frequency of each part is the subtotal divided by the total number of parts in the sample. The relative frequencies can then be classified by cumulative proportion of the total sample, into classes such as A, B and C parts.

Table 3.1 provides summary Pareto data of critical repair parts replaced on a sample of n = 276 systems over a 54 month period. The table shows that five of the parts out of 142 types in the sample caused 2734 of the system failures, or 38% of the total failures.

Total types of parts replaced: 142

Total usage of parts replaced: 7,281

Part Class	Number of Types in Class	Number of Failures in Class	Contribution to Total Failures
A	5	2734	38%
B	10	1577	22%
C	127	2970	40%

Table 3.1 Pareto Analysis of Failure Caused By Parts

It should be noted that one part had the highest individual contribution to system failure (16%), but this may have been due to special circumstances, explained in Appendix C. The remaining A parts were between 3-7% (each) of the total failures; the B parts ranged from 1.6 to 2.8% of the total failures. Nine of the C parts contributed between 1-2% of the total system failures, and the remainder of the parts each contributed to less than 1% of the system failures. Further reliability analysis and product improvement may be warranted on the one part that contributed to 16% of the system failures. Based on these results, it is safe to conclude that the system is sufficiently complex enough to assume independent failure causes. We can therefore classify this system as a "complex repairable system" (Crow, 1975). The detailed data is presented in Appendix C.

E. SUMMARY

Considerable data is available from both the Marine Corps and the U.S. Army available for use with reliability engineering theoy. Interarrival times for system failures can be derived from either the MIMMS-AIS database, or the Army TACOM Sample Data Collection. These two databases do not have the same structure, therefore the assumptions and procedures for screening

the data for each are not interchangeable. The main purpose of this chapter is to identify interpretations of the MIMMS-AIS data. Similar data is available from the U.S. Army.

Knowing the interarrival patterns of the system failures, the reliability concepts discussed in Chapter II are applied to the data to determine the condition of the equipment, and make projections about the future. Forecasted failures are then used for decision making between alternative replacement, overhaul or minimal repair policies, or to evaluate the effectiveness of extended service life programs.

When using idealistic models, it is critical to consider the assumptions and the source of the data. Knowing how the data is generated helps to identify causes of variability, and helps eliminate "suspect" data prior to drawing conclusions. It is important to be able to recognize the "garbage in - garbage out" situation, caused by erroneous input or missing data. This chapter provids examples of some of the common causes of inconsistencies in MIMMS-AIS data. Large databases can be screened for such inconsistencies by using logic flags and indicators designed to highlight such situations. Proper use of the statistics described in Chapter II depends on correct ordering, sample sizes, and truncation of the data, as well as the knowing assumptions and limitations of the models. MIMMS-AIS provides the historical data on Marine Corps unique equipment for reliability analysis.

The next chapter presents a cost-based model that may be used to project the costs of expected failures over future intervals.

IV. DESCRIPTION OF THE MODEL

A. INTRODUCTION

This chapter outlines a model developed for this thesis which combines system reliability with the cost of failures that are used when evaluating alternative "do-nothing" or overhaul decisions. The system "cost of failure" used here is defined as the direct costs associated with restoring the system to operational status. For simplicity, each Equipment Repair Order (ERO) reflects a single system failure, such that the cost of replacement parts plus the cost of direct labor are taken to be the failure costs for a repair of a single system. The model presented in this chapter uses historical maintenance data on a system using the time to failure data, in order to obtain maximum likelihood estimates of the parameters of the ROCOF, $\rho(t)$, presented in Chapter II. The "do-nothing" alternative means that the system is restored by minimal repairs each time it fails. As the system begins to fail more frequently due to deterioration, the cost of owning that system may increase at an increasing rate. At some point, it is more economical to overhaul or replace the system. This chapter outlines the steps used to analyze a "do-nothing" versus overhaul decision about a Marine Corps system based on MIMMS-AIS data. The next chapter presents a case study of the M998 HMMWV using the model described in this chapter.

Since no HMMWV's have been overhauled, no data exists on the reliability of the system after overhaul. Lee, Puzzuoli and Hoogterp (1975) have developed a simulation program which can be used to analyze the effects of overhaul on military vehicles for various overhaul intervals and percentage of components replaced. Their conclusions show that under most conditions, a system is restored to about 90% of its original, or *as new* reliability after overhaul. The US Army Tank-Automotive command assumes that overhaul extends the system life to roughly 80% of its economic useful life before overhaul. After overhaul, the system failure rate increases with age at roughly the same rate as it did prior to overhaul.

B. DESCRIPTION OF THE MODEL

This analysis can be described in two parts; first, analysis of the system reliability which involves estimation of the ROCOF, and second, the cost estimate of the do-nothing alternative. The MIMMS data provides for computing both the reliability and costs for the analysis on the existing system. The cost estimates for the overhaul or rebuy alternatives are beyond to scope of

this thesis; therefore, cost assumptions regarding overhaul and rebuy alternatives is based on the appropriate Program Manager's estimates.

1. Estimation of the Rate of Occurrence of Failures

The objective is to estimate the system rate of occurrence of failures (ROCOF) given by $\rho(t)$ as described in Chapter II, in order to obtain a quantitative measure of where the system is in its life-cycle, i.e., in its "useful life" or deterioration phase. The integral of the ROCOF, given by equation (2-8) provides an estimate of the expected number of failures, V(t), within a defined interval (Ascher and Feingold (1984), Sadlon (1993), Barlow and Proschan (1965)). Expected costs of those failures can be multiplied by the number of failures in the intervals to determine total costs. The steps involved in the ROCOF model are:

Step 1. Obtain the Total Time to System Failure (TTSF) data on the system. If data is available starting from time zero, then equations (2-10) through (2-13) can be used to obtain the MLEs for β and λ . If data is only available for a limited history, then the $TTSF_i$ are rescaled with the "first" failure in the observed interval taken to be time = 0 for computational purposes. The resulting MLEs will actually describe the failure intensity for the interval in which the TTSF data was taken.

Step 2. Investigate for major contributing causes of repeated system failures. The purpose is to prevent making an overhaul/replace decision based on the contribution of a single component or small group of components which are causing most of the system failures. A Pareto analysis is used in this thesis to establish whether the system is sufficiently complex enough to verify whether a small group of parts dominate the total system failure causes or not. Other techniques such as fault tree analysis, failure mode effects and criticality analysis (FMECA), or a review of Quality Deficiency Reports (SF-368) may provide more detailed analysis of contributing failure causes.

Step 3. Perform trend analysis, using either the LaPlace trend test, the MIL-HDBK-189 test or graphical plotting to determine whether the system failure rate shows constant or deteriorating trends.

Step 4. If the failure rate shows a constant trend, continue to use current (linear) O&M cost projections when evaluating decision alternatives. A constant failure rate would assume the HPP failure model, therefore linear cost assumptions would be appropriate.

Step 5. If the failure rate shows an increasing trend, estimate the ROCOF by calculating the MLEs for β and λ presented in Chapter II. The next section presents a spreadsheet model which computes individual system MLEs as well as pooled MLEs for the sample. Costs will increase as a function of the expected number of failures in time t (*Note*: Depending on the value of β, i.e., when $\beta \approx 1$, the V(t) may appear to be nearly linear, in which case it may be simpler to use a linear cost approximation. Whether to use the linear assumption or not would be based on the fit of a linear trendline to the ROCOF, and the resulting coefficient of determination).

Step 6. Forecast the expected number of failures for future periods as a basis for comparison to the overhaul/replace decisions. Bain (1978) provides further information on prediction intervals.

The steps listed above can be summarized by the flowchart shown in Figure 4.1. It depicts the steps to decide whether to use the HPP or NHPP assumptions:

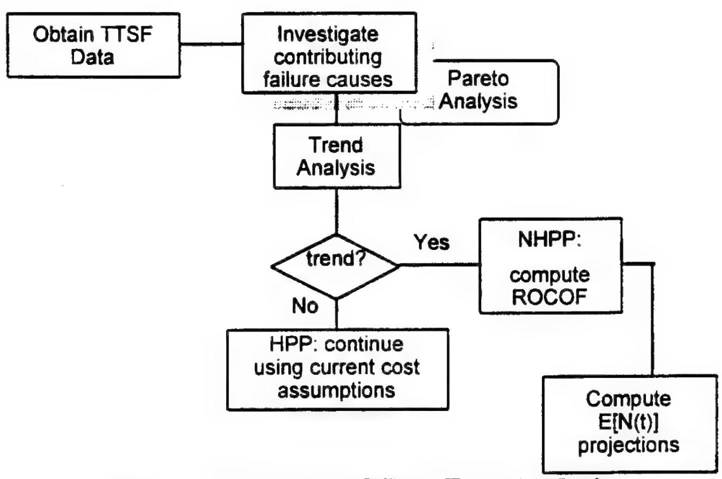

Figure 4.1 System Failure Rate Analysis

2. Cost Analysis

The underlying assumption in the cost analysis is that the number and frequency of failures increase as mechanical systems age, and therefore the cumulative costs associated with the failures do also. For this analysis, only the variable costs of parts and labor associated with the ERO are considered, assuming that fixed costs for the systems associated with either alternative are the same.

Simulation is used to evaluate total cost distribution outcomes of the decision alternatives. This way, the probabilities associated with the expected values of the decision alternatives are used to make more informed decisions, not just the expected values alone. The simulation is based on the frequency distributions of the input parameters. Frequency distributions of the MIMMS data are constructed from the costs (replacement parts and direct labor hours) fields from each ERO in the sample. These frequency distributions are then run through "Best Fit," a statistical software package which provides the descriptive statistics and most likely distributions of the data. Once the cost distributions are obtained, they can then be input into the appropriate cost equations and run through commercial software such as "Crystal Ball" (Decisioneering, 1993) or "@Risk", which are spreadsheet add-in programs. These programs run automatic "Monte Carlo" simulation on the input parameters to provide a solution *output distribution.* The output distribution is more meaningful for decision making than deterministic values. In the case of the MIMMS-AIS data, the labor hour and ERO cost data are run through Best Fit to obtain the input distribution for use with Crystal Ball. For the purposes of this thesis, only labor and replacement parts costs are considered, assuming that overhead and fixed costs for either the "do-nothing" or overhaul/buy-new alternatives are the same.

The cost per system failure C_F, obtained from the ERO cost distributions, is defined as:

$$C_F = C_R + C_L \tag{4-1}$$

where C_R is the cost of all replacement parts applied to the ERO, and C_L is the cost of direct labor. Direct labor hours are recorded on the ERO, and reflect the total mechanic-hours used to restore the system. It is not necessary to assume that one or "n" mechanics performed the repairs to compute total labor hour costs. Note that labor *costs* are not recorded on the ERO; rather, labor hours. Labor costs are derived based on several assumptions. Here, it is assumed that equipment is repaired by Marines of rank E3 through E5, with probabilities of 0.45, 0.35 and 0.20 respectively, that each rank performs repairs. Therefore, a "weighted" labor rate based on the composite hourly rates times the probabilities above is used to calculate labor costs for each ERO. The composite hourly rates for paygrades E3, E4 and E5 are \$10.29, \$12.33, and \$14.46, respectively. The weighting factors above are based on the approximate ratios of these ranks within a typical maintenance shop; therefore the weighted rate used is \$11.84/hour. Pay and benefits data is based on FY90 dollars (MCO P7000.14,1991).

The total costs for a future projected period (C_T) is determined by the expected number of failures times the cost per failure C_F, plus scheduled maintenance costs, C_S, or:

$$C_T = V(t)C_F + C_S \tag{4-2}$$

where V(t) is given in equation (2-8). This formula is used to calculate the annual maintenance costs of the do-nothing alternative.

C. MIMMS DATA PREPARATION

The analysis of the MIMMS-AIS data was done on a personal computer, using a combination of Microsoft Query, a database program, and Microsoft Excel, a spreadsheet program. The query program is used to further refine and filter the data prior to use with the spreadsheet. The spreadsheet program is used for ease of computations and graphical plotting.

In order to conduct the analysis, the raw MIMM-AIS data has to be converted to a spreadsheet format. The most important data for the reliability analysis is the time to system failures (TTSF), which in the case of MIMMS-AIS is the primary meter-reading (equipment operating time) field. Other relevent data is needed to segregate fleet populations, such as WestPac equipment from U.S. East Coast equipment, since systems in different geographic regions will show different failure patterns. Other MIMMS-AIS data such as parts replacements, parts costs, and labor hours are needed in order to compute the cost distributions associated with system failures. The following database fields are needed to conduct the analysis presented in this model:

Field Name	Description
RAC	Geographic Regional Activity Code.
ITEM	The equipment type, designated by its nomenclature, or identification number, model number or other descriptive information.
SERIAL #	The equipment serial number.
DATERECIN	The date the Equipment Repair Order was initiated, and the equipment was received in shop for repairs.
DATECLOS	The date the ERO was closed, repairs completed.

METER	The meter reading (mileage). Chapter III discussed the fact that this should be the mileage at failure, however, MIMMS reflects the mileage at restoration. These records represent the system $TTSF_i$ for the system.
PARTNAME	The repair parts used to restore the system. Presumably, parts are replaced due to wearout/failure.
QTY	Quantity of parts replaced. This is multiplied by the parts cost to obtain total cost of a particular component type replacement.
PARTCOST	Charges for replacement parts. Note that a factor of 40% is used for secondary repairables, such as engines and transmissions, since the cost in MIMMS-AIS reflects the price of a new secondary repairable. In practice, the large majority of these are rebuilt for about 40% of the new cost. (TACOM, 1985)
MILABHRS	Total direct labor hours expended during repairs under each ERO.
ECHELON	Echelon of repair of the ERO. Note that only 2nd echelon EROs should be used to compute TTSF; mileages for higher echelon repairs should not be included. 3rd and 4th echelon repairs are presumed to be due to the same failure which initiated the 2nd echelon ERO.

Other MIMMS-AIS fields and separate computed fields (such as requisition lead-times, logistic delay times, etc.) may be used for more detailed analysis. Since data records are displayed as spreadsheet rows, logic flags are used in the spreadsheet to differentiate records associated with the EROs or serial numbers contained in the previous record. Appendix A presents the logic flags used in the spreadsheet to further filter the data, and to count records meeting specified criteria.

1. Segregate Different Populations

In order to obtain meaningful results, the sample population of the system in question should be as homogeneous as possible. When setting up the data for analysis, any database codes, fields or flags that distinguish between the system manufacturing date, location, variant, or model number should be segregated, depending on the comparability of the items. In the case of the HMMWV's, the Marine Corps has many different variants which are used under different operating conditions. For example, even the data for a single variant, such as the M998, includes

both the "generic" vehicles, and radio variants which will show much different operating characteristics from each other, such as mileage or engine wear. Further, major geographic or regional factors may need to be considered, since environmental conditions will have varying degrees of effect on the life of the equipment. Therefore, the analysis may require the data on like systems to be filtered into homogeneous populations prior to drawing any meaningful conclusions.

2. Eliminate Questionable Data

Chapter III discussed problems with MIMMS-AIS meter reading data. Prior to conducting any of the analysis requiring system TTSFs, suspect data should be filtered out. Logic flags are used in the spreadsheet to highlight:

- "Suspect" meter readings of "999999," "0" or "1" miles.
- Meter readings which are less than the prior meter reading on the same system.
- Meter readings that are unreasonably higher than the prior meter readings. Such entries are often due to the tenth digit being included when the mileage was recorded in MIMMS, e.g. an odometer reading of 17184.3 was incorrectly entered as 171843 miles. (Refer to Chapter III, section C).

3. Perform Pareto Analysis

The decision to overhaul or replace a system is based on the assumption that the existing system is deteriorating beyond economical repairs. If only a few components are contributing to the causes of the system failures, then the attention should be focused on improving the reliability of those few but vital components. Crow's (1975) MLEs discussed in Chapter II assumes that the system is sufficiently complex and that no single part or groups of parts contribute to the majority of the system failures. The MIMMS replacement part data is analyzed using Pareto analysis, and the results provide the basis for the validity of that assumption. As Chapter III showed, the Pareto analysis on the HMMWV indicated that the "sufficiently complex" assumption could be used.

4. Perform Trend Testing

Equation (2-9) provides the LaPlace test statistic (U) which indicates trends in the failure data. Prior to making assumptions about an HPP or NHPP failure rate, this statistic should be computed for the systems in the population. A graphical plot of the cumulative times to failure versus cumulative number of failures will also indicate whether a system is improving, in a steady-state, or deteriorating.

5. Compute MLEs β and λ and Confidence Bounds

Equations (2-12) and (2-13) are used to compute the conditional MLEs for β and λ for time truncated data. Confidence bounds for β are given by equations (2-14) and (2-15); confidence bounds for λ by equations (2-16) and (2-17). The input data consists of the Total Time to System Failure ($TTSF_i$) data for each i-th failure for each q-th system.

The spreadsheet format on the next page contains the formulas used in the model for determining MLEs for β and λ, along with their respective upper and lower confidence limts for a sample population. It contains simulated failure times ($TTSF_i$) for K=3 systems and N=10 failures each. To use the model, the $TTSF_i$s for each system are copied from the MIMMS-AIS data and inserted into the appropriate columns with the "$TTSF_i$" headings. All other values are automatically calculated based on the time truncated, conditional MLE formulas and χ^2 confidence intervals presented in Chapter II. The number of columns can be copied for as many systems as required, subject to the limitations of the software and computer memory.

When data is not available from the system "birth" ($T_0 = 0$), the $TTSF_i$s must be rescaled as discussed in Chapter II. The data for the three sample systems was purposely designed to show one system with an "improving" failure rate, one with a constant failure rate, and one with a deteriorating failure rate.

The spreadsheet computes the individual system MLEs for β and λ, which are recorded just below the system serial numbers. At the top of the spreadsheet, the pooled values of β and λ are provided for the entire sample. The pooled values are used to compute the ROCOF for the sample population. If the individual systems show a wide range of differences, it may not be appropriate to use the entire sample to compute the pooled MLEs. For example, if the results indicated that

DATA TOTALS:	
Σ Nq:	27
Σ ln(TTSFi)	263.3
Σ TTSFi^β	5E+06
Σ ln(TTSFn/TTSFi)	21.36

SAMPLE RESULTS

		LCL	UCL
β hat:	1.264	0.892	1.689
λ hat:	5.46E-06	3.86E-06	7.53E-06

System 1
LaPlace: 1.570
β= 2.24
λ= 4.64E-10

Time to System Failure (i)	TTSFi	Scaled TTSFi	i	ln(TTSFn/TTSFi)	ln(TTSFi)	TTSFi^β
1	22000					
2	32000	10000	1	1.361	9.210	114053.9
3	38000	16000	1	0.891	9.680	206620.9
4	40000	18000	1	0.773	9.798	239797.9
5	46000	24000	1	0.486	10.086	344986.8
6	52000	30000	1	0.262	10.309	457429
7	56000	34000	1	0.137	10.434	535854.5
8	58000	36000	1	0.080	10.491	576011
9	60000	38000	1	0.026	10.545	616761.7
10	61000	39000	1	0.000	10.571	637352.5
Σ(TTSFi)		245000				
Σ(Ni)			9			
Σ ln(TTSFn/TTSFi)				4.016		
Σ ln(TTSFi)					91.13	
Σ TTSFi^β						3728868

System 2
LaPlace: -1.382
β= 0.87
λ= 0.00093

Failure (i)	TTSFi	Scaled TTSFi	i	ln(TTSFn/TTSFi)	ln(TTSFi)	TTSFi^β
1	22000					
2	25000	3000	1	2.565	8.006	24891.22
3	27000	5000	1	2.054	8.517	47481.51
4	29000	7000	1	1.718	8.854	72655.91
5	31000	9000	1	1.466	9.105	99829.72
6	34000	12000	1	1.179	9.393	143620.7
7	40000	18000	1	0.773	9.798	239797.9
8	47000	25000	1	0.445	10.127	363259.2
9	55000	33000	1	0.167	10.404	516006.9
10	61000	39000	1	0.000	10.571	637352.5
Σ(TTSFi)		151000				
Σ(Ni)			9			
Σ ln(TTSFn/TTSFi)				10.367		
Σ ln(TTSFi)					84.78	
Σ TTSFi^β						637352.5

System 3
LaPlace: 0.000
β= 1.29
λ= 1.18E-05

Failure (i)	TTSFi	Scaled TTSFi	i	ln(TTSFn/TTSFi)	ln(TTSFi)	TTSFi^β
1	24000					
2	28000	4000	1	2.197	8.294	35809.92
3	32000	8000	1	1.504	8.987	86017.9
4	36000	12000	1	1.099	9.393	143620.7
5	40000	16000	1	0.811	9.680	206620.9
6	44000	20000	1	0.588	9.903	273965.2
7	48000	24000	1	0.405	10.086	344986.8
8	52000	28000	1	0.251	10.240	419219.9
9	56000	32000	1	0.118	10.373	496317.7
10	60000	36000	1	0.000	10.491	576011
Σ(TTSFi)		180000				
Σ(Ni)			9			
Σ ln(TTSFn/TTSFi)				6.973		
Σ ln(TTSFi)					87.45	
Σ TTSFi^β						576011

half of the systems show "improving" trends in the failure data, while the other half were deteriorating, the MLE for β would probably be very close to one, indicating a fleet-wide linear failure intensity. Therefore, additional analysis would be required to determine the causes of the differences in the failure intensities (i.e., operating conditions or age) of the equipment.

A plot of the simulated data for the three systems represented in the spreadsheet is presented in Figure 4.2. The plot is provided to illustrate the shapes of the cumulative failure curves based on systems at various stages in their life-cycles, and is useful for estimating the general condition of the equipment:

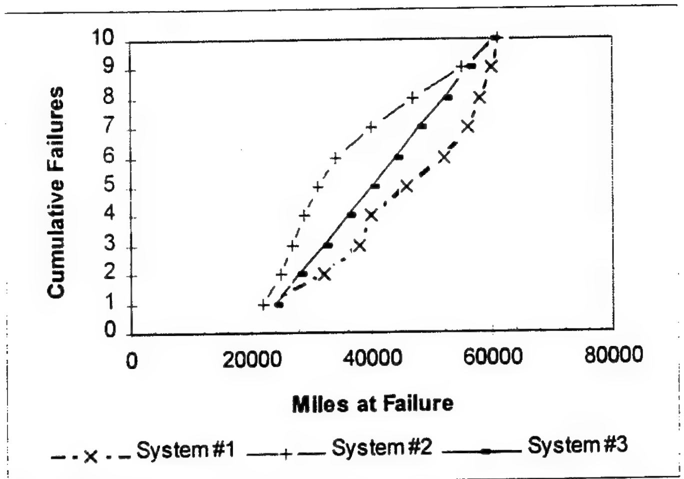

Figure 4.2 Sample Failure Plots for Simulated Data

As shown in Figure 4.2, System #1 is deteriorating, since it has an increasing failure intensity based on output from the spreadsheet model. Its value for β = 2.24, and LaPlace (U) = 1.57. Graphically, the $TTSF_i$s show a convex cumulative failure curve with respect to the origin. System #2 has β = 0.87 and U = -1.38, indicating a decreasing failure rate (system improvement); and graphically has a curve concave to the origin. System #3 has β = 1.2, indicating a nearly linear failure rate, and U = 0, indicating no trend in the failure arrival patterns. In general, the "status" of a system during its life-cycle can be described based on the values of U and β, summarized as shown in Table 4.1:

Life-Cycle Phase	β Value	LaPlace Test Statistic (U)
Burn-in, debugging, work-hardening	$\beta < 1$	$U < 0$
Useful life/ random failures	$\beta \approx 1$	$U = 0$
Deterioration	$\beta > 1$	$U > 0$

Table 4.1 Interpretations of Values for β and U

The data truncation of the $TTSF_1$'s and $TTSF_n$'s must be considered for the systems in order to reach meaningful conclusions. For example, comparing failure truncated data on a system with ten failures between zero and 20,000 miles with another system which had ten failures between 80,000 to 90,000 miles would not result in meaningful conclusions (Crow,1975). The first system might be in its "burn-in" phase and would show an improving ROCOF, while the second system may be in a deterioration phase and would show a deteriorating ROCOF. In both cases, the true values of β and λ would be different. Evaluating "brackets" of TTSF data for the same systems over different intervals in the life-cycle will yield different values for β and λ, as the "bathtub" curve shown in Chapter II indicates. For this analysis, time truncated data for only those vehicles with sufficiently high mileages (vehicles with more than 40,000 miles) is used, so that the systems used to derive the MLEs are assumed to be in the same phase of their life-cycle. As a further check, a comparison of the vehicle-by-vehicle LaPlace statistic may be used to ensure that systems are in the same phase of their life-cycles, prior to drawing conclusions.

D. FORECAST EXPECTED FUTURE MAINTENANCE COSTS

Once the MLEs of β and λ are obtained, the ROCOF $\rho(t)$, given in equation (2-6) can be defined. If the LaPlace test statistic indicates that a system is deteriorating, it is assumed that the system will continue to deteriorate at the rate $\rho(t)$ even when minimal repairs are performed. The expected number of failures are then extrapolated using V(t) for a future period of time. Equation (3-2) can be used to forecast future costs over intervals, such as simulated annual mileage equivalents. A distribution of annual mileage equivalents can be approximated from the

MIMMS data by computing the difference between individual vehicle meter readings over 365 day periods. For this thesis, it is assumed that if the system is deteriorating, that the ROCOF $\rho(t)$, can be extrapolated using the same values for β and λ over a reasonable number of future periods (Bain, 1978).

1. Cost Stream Assumptions for the Present System

If the system is deteriorating, it is assumed that maintenance costs will increase rapidly under the "do-nothing" alternative. Fuel, crew, and overhead costs such as facilities and war reserve spares costs are assumed to be the same for either alternative, so they are not considered in this analysis. If they are not the same for each alternative, then the additional costs/savings must be reflected in the break-even analysis. The "failure" cost is defined in equation (4-1). The forecasted annual maintenance cost is defined in equation (4-2) as the number of expected failures per year times the cost per failure plus scheduled maintenance costs. For this model, semi-annual scheduled preventative maintenance is assumed. The expected number of annual failures is driven by forecasted annual mileage. Of course, annual mileage varies widely for individual vehicles and among fleets of vehicles, therefore a *distribution* of annual mileage is used as an input variable into the total cost equation, and evaluated using the "Crystal Ball" software or other simulation techniques. For example, the annual mileage distribution from the MIMMS data on the HMMWVs was run through Best Fit, resulting in a Lognormal distribution with $\mu = 6970$, and $\sigma = 7650$ miles. Other assumptions include:

- The distribution and parameter values of the input variables based on the MIMMS data are presented in Appendix B.
- Nominal discount factors for net present value analysis are obtained from OMB Circular A-94 annual supplement (OMB, 1993).
- Costs are in then-year dollars.

2. Cost Stream Assumptions for the Overhaul/ Buy New Alternatives

The decision whether to keep the current system and continue to perform minimal repairs (the "do-nothing" alternative) or to buy or overhaul can be made using break-even analysis of the O&M cash flows. Although cost estimates may be available for the unit costs of rebuild or buy-new options, estimates about annual O&M costs for those alternatives may not be available, therefore a few assumptions need to be stated. For this analysis, the annual O&M costs associated

with the overhaul alternative are assumed to be the same as when the system was "new." The same cost stream starting at T_0 (not including inflation factors) is then added to the cost of overhaul, and is used for that alternative. The effect of the life extension is most likely unknown, but may be estimated as 80% of the original useful life.

Ideally, the reliability data and costs of the existing system would be used to compute the reliability and costs after its overhaul. That is, the same failure intensity for the original system would apply after overhaul, reset to "as new" or T_0, given that brand new but same components are replaced. (In most cases, better quality parts or component improvements are replaced during overhaul). Since O&M costs are not known for the system after overhaul, the relationship used by the U.S. Army TACOM shown in equation (4-3) is used to estimate the *as new* HMMWV O&M costs reset to T_0 (TACOM, 1989). For the HMMWV, the annual cost equation is:

$$C = [mA + b]x + k \tag{4-3}$$

the values given for the M998 HMMWV for the variables are:

m: slope = .0554

b: constant = .1436 \$/year

k: constant = 318 \$/year

A: Age = age of the vehicle in years

x: mileage: mileage is simulated using annual mileage equivalents, as discussed in the previous section.

Equation (4-3) above *does* account for fuel, crew and other costs, however since these costs are reflected in all three variables (slope, intercept, constant), there is no way to rescale this equation to only reflect parts and labor (i.e., direct maintenance) charges. Since it is the only data available to approximate HMMWV costs since $T_0 = 0$, then it is used as the best available cost comparison. Ideally, the system's actual life-cycle costs would be known for such analysis.

3. Rough Estimates

Equation (2-18) provides the optimal overhaul/replace time, which minimizes the expected maintenance costs of minimal repairs (Barlow and Proschan, 1965). It is an extremely simplified equation, and should only be used as a guage for rough estimates. The parameters β and λ which were calculated earlier are input into (2-19) and the optimal system replacement interval T^* is

obtained. Equation (2-19) similarly, is a highly simplified equation which approximates the estimated life expectency of a system based on linearly increasing annual maintenance costs. These figures can be used as a check to the break-even analysis, but should not be used exclusively for decision making purposes.

E. SUMMARY

Maintenance data from MIMMS-AIS can be used to estimate the failure intensity of Marine Corps systems, using the spreadsheet model presented in this chapter. MLEs for the parameters of the ROCOF can be used to forecast the expected number of failures over future intervals. The MIMMS-AIS data also provides measures of the direct costs of failures, which are multiplied by the expected number of failures to obtain total annual cost forecasts for systems. The advantage to using the ROCOF forecast for future periods rather than simple linear approximation methods is that deterioration may cause failures to occur at increasing rates, in which case an exponential relationship may provide a more accurrate basis for decision making. Using the forecasted cost streams, break-even analysis can be used for decision making between the "do-nothing," overhaul, or buy-new alternatives. The next chapter presents a case analysis of this model using MIMMS-AIS data for a sample population of HMMWVs from West Coast Marine Corps units.

V. CASE ANALYSIS OF HMMWV FAILURE DATA

A. PURPOSE

The purpose of this chapter is to present an example of the model presented in Chapter IV applied to MIMMS data on the M998A1 series HMMWV. The HMMWV is currently in its *mid-life*-cycle in the Marine Corps; most of the HMMWVs are roughly eight years old. An extended service-life program (ESP) is currently being programmed for the HMMWV fleet, which includes a block upgrade of most major components. Applying this model could validate the need and identify a time horizon when the ESP becomes economically desirable. For the purposes of this chapter, the ESP is referred to in terms of "overhaul," although it actually entails more than the overhaul, as defined in Chapter II. The objectives include; 1) identify whether the sample of HMMWVs shows any trend in the failure data, 2) computation of the parameters β and λ, so that expected failures and failure intensities can be estimated, 3) provide supporting estimates to help the program managers make a decision about when to perform the ESP.

B. ESTIMATION OF THE HMMWV RATE OF OCCURRENCE OF FAILURES

This section discusses the process described in Chapter IV section B, 1, which is used to convert the MIMMS data into a form that can be used to obtain the MLEs needed to estimate the ROCOF and expected failure functions.

1. MIMMS-AIS Data Preparation

The first step is to filter the MIMMS-AIS data to a form that can be used with the *MLE Estimation Spreadsheet* model to compute the individual system MLEs, "pooled" sample MLEs, and the LaPlace test statistics. The specific data requested for this thesis were the MIMMS-AIS database records for "critical maintenance" EROs on the M998 HMMWV. It is assumed that parts with "Combat Essentiality Code" (CEC) = 0, 1, 5, or 6 would cause system operational mission failures if they failed. Further, Material Usage Code (MUC) = "7" was specified (repair parts and secondary repairables). The other MUCs specify scheduled maintenance parts (such as filters), collateral equipment, and modifications; these do not constitute mission critical system failures. All maintenance category codes were included in the initial query. All maintenance category codes were included, although only maintenance category codes "M" and "P" in MIMMS reflect

critical maintenance, however these status codes are normally downgraded to "routine" after the critical repairs are completed and prior to closing the ERO, as discussed in Chapter III.

Records with suspect meter-readings were filtered out prior to analysis, since these cause erroneous failure results. Lastly, EROs that showed a defect-code indicating that the primary meter was replaced were deleted from the data file prior to analysis. In all, roughly 25% of the raw data was purged before any analysis even started.

The data file used for this thesis contained records only for the U.S. West Coast regional units. After eliminating the "bad" data, a total of 3040 records representing 276 unique vehicle serial numbers resulted. The 3040 total records reflects both the fact that most serial numbers had multiple ERO history files over the 54 month sample period, and that most EROs had multiple replacement parts (which are separate database records) recorded against them.

The database records appear as *rows* in both the Query and Excel (spreadsheet) software, which represent either unique Equipment Repair Order (ERO) records, or the parts ordered under the ERO. (One ERO is always associated with one serial number for principal end items). For example, if seven different parts were requisitioned under one ERO, seven "rows" of data will appear all with the same ERO and equipment serial number in the spreadsheet. These records will all show the same meter-reading, labor-hours and open and closed dates for the ERO. The parts-trailer records (i.e., part name, cost, order-date) are unique for those parts. To illustrate, an extract of seven fields from the raw data is provided below. The extract shows how the raw data (selected fields) file appears after sorting:

RAC	SERIAL#	ERO	METER	DLHOURS	PARTNAME	PART COSTS
MIM001	532282	PG433	18151	2	PUMP ASSEMBLY,POWER	40.21
MIM001	532282	PG433	18151	2	DOOR ASSEMBLY,VEHIC	89.22
MIM001	532282	PG433	18151	2	GASKET	3.38
MIM001	532282	PG519	18152	4	RADIATOR,ENGINE COO	329.00
MIM001	532282	PG581	12544	10	PARTS KIT,HAND BRAK	22.63
MIM001	532282	PG581	12544	10	SEAL,NONMETALLIC SP	2.52
MIM001	532282	PG424	20860	0	ROTOR,DISC BRAKE	7.64
MIM001	532282	PG424	20860	0	PARTS KIT,BALL JOIN	16.45
MIM001	532282	PG424	20860	0	STARTER,ENGINE,ELEC	322.00
MIM001	532284	WNN20	25056	4	ROTOR,DISC BRAKE	7.64
MIM001	532284	WNN20	25056	4	IMPELLER,FAN,AXIAL	185.00

The first three records in the above sample all pertain to a unique ERO on the same serial number (532282), under which three parts were ordered. The fourth record is for a new ERO on

serial number 532282. The tenth record is a unique serial number (532284) and a unique ERO, and starts a new data record.

The next step was to sort the entire database by; 1) serial number, 2) date-received-in-shop, 3) primary meter reading. Although Chapter III discussed problems with the ERO open and close dates and the order in which the meter readings would appear, it turned out to be easier simply to sort the meter readings for each serial number in ascending sequence. This procedure does not violate the chronological ordering discussed in Chapter II, since the meter readings increase with time/usage. The chronological sequence of the various open and close dates of the EROs becomes too much of an administrative burden to be concerned with, and does not have an impact on the failure data.

Four primary logic counters were used either to count records that met a criteria, or as flags to highlight other interests:

NAME	**PURPOSE**
FLAG 1	Distinguishes unique EROs and unique serial numbers. Values are "2" if the record is both a unique ERO and serial number than the previous record. "1" if the record is a unique ERO but same serial number as previous record; "0" if the record is a parts-trailer for the same ERO as the previous record.
FLAG 2	Compares the date closed of the next unique ERO number to the open date of the current ERO record; used to highlight suspect data.
#FAILURES	Counters used to indicate the total number of failures accrued for a unique serial number. This criteria is used to find serial numbers with greater than or equal to "N" failures in order to obtain failure truncated data.
CUML ERO$	Accumulates the total cost of parts on an ERO-by-ERO basis. Straight parts charges for individual items are contained in the raw MIMMS-AIS data, and need to be summed for each ERO.

Other minor conversions are required, such as for Julian dates, parts costs and labor-hours. These formulas are provided in Appendix A.

Once the data is prepared, the next step is to identify serial numbers with sufficient usage and a sufficient number of failures to obtain the MLEs for β and λ. There is a tradeoff between the number of unique vehicle serial numbers (K) which have a specified number of recorded failures needed to obtain confident pooled MLEs, and the number of observed failures (N) recorded against each serial number. The greater the value of N desired, the smaller the number K of serial numbers will meet that criteria in the database. For N too low, the MLE results are meaningless. The key is to select a data set which yields reasonably high values for N and K, since the degrees of freedom that determine the confidence intervals around the MLEs are determined by the total number of pooled failures (M). Recall that equations (2-14) through (2-17) are the lower and upper confidence limits for β and λ, respectively, and all have degrees of freedom driven by M.

In Excel, the "AutoFilter" option allows such queries to be performed easily. To get an idea of the range of data, first records are filtered with "greater than" specified mileages, for example, show records with greater than 50,000 miles. This step provides a basis for where the data should be time truncated for the analysis. The next step is to identify individual system serial numbers with a certain number of failures, e.g., $N \geq 8$ failures. This is done by setting the criteria for the "# FAILURES" column to a specified value. Within the file used for this thesis, among the 276 unique serial numbers, only 19 of those showed greater than seven mission critical failures *recorded*. Only two serial numbers showed $N \geq 10$ failures. The tradeoff of K and N for this analysis resulted in $K = 32$ systems with $N \geq 6$ failures each. Any less than six failure observations would not have allowed for a meaningful analysis, since trends in the total time to system failure data ($TTSF_i$s) would not be apparent based on fewer data points.

Finally, the meter reading data ($TTSF_i$s) for each of the $K = 32$ serial numbers with $N \geq 6$ failures was extracted from the data file, and copied into the MLE estimation spreadsheet similar to the one presented in Chapter IV.

A separate database file provided by the HMMWV inventory manager contained manufacturing and fielding dates of the Marine Corps' HMMWVs. A query for these 32 serial numbers indicated that all of them were fielded during 1986. Since all of the systems are the same age (eight years old) and operated in West Coast Fleet Marine Force Units, it is assumed that they all are in roughly the same stage of their life-cycle.

2. Investigate for Dominant Failure Causes

Prior to beginning any detailed trend or reliability analysis, primary failure causes are investigated in order to eliminate the potential for making unnecessary program decisions. One purpose is to establish that the system under question is sufficiently complex enough to use the assumptions stated in Chapter III. Another reason is to avoid making a decision to overhaul or replace a system due to frequent failures, when the primary cause of those failures may be due to a few but critical substandard components. For this thesis, a Pareto analysis was done for all of the parts in the database. This process was simplified using the "Pivot Table" add-in program in Excel, which creates a transposed array of specified data fields, and automatically totals any fields desired, either vertically or horizontally. Using the pivot-table add-in, the sample data was used to create a Pareto distribution of parts sorted by usage. Appendix C contains the results of the Pareto analysis.

3. Computation of the Maximum Likelihood Estimators for β and λ

Maximum likelihood estimates of β and λ for each system were obtained using the MLE Estimate Spreadsheet presented in Chapter IV, based on the TTSF data for the K=32 systems. The box at the top of the spreadsheet shows the pooled MLEs for the sample population. An extract of the MLE estimation spreadsheet for this data set is contained in Appendix B. Values for the pooled MLEs are summarized in Table 5.1:

Parameter	LCL	MLE	UCL
$\bar{\beta}$	1.393	1.597	1.812
$\bar{\lambda}$	4.3×10^{-7}	5.0×10^{-7}	5.7×10^{-7}

Table 5.1 Conditional Pooled MLEs for the Sample

4. Trend Analysis

Chapter IV introduced the sample MLE estimation spreadsheet which computed the LaPlace test statistic (U) for trends of the $TTSF_i$ data, based on equation (2-9). Two systems of the 32 total systems had LaPlace statistics indicating decreasing failure rates (DFR), or U < 0. Speculation might suggest that these two serial numbers might be vehicles assigned to unit Commanding Officers. Traditionally, Marine Corps motor-pools tend to place the highest

emphasis on the CO's vehicle. All of the other systems had LaPlace statistics indicating system deterioration, or increasing failure rates (IFR), where U > 0. Results are summarized in Table 5.2. Plots of the mileage to cumulative failures (see Appendix B) also indicated increasing failure rates. Based on the predominant positive values of the LaPlace statistics for the individual systems, the conclusion is that this HMMWV sample population is deteriorating. The NHPP assumption is made regarding the failure intensity of the sample population, and therefore the ROCOF model is used to evaluate the failures, and to forecast expected failures for future intervals.

q	Serial #	LaPlace:	β	λ	Trend
1	535199	2.038	1.851	6.00E-07	IFR
2	535212	1.452	1.448	1.50E-05	IFR
3	535393	2.497	1.125	0.00019	IFR
4	537144	2.041	1.939	1.90E-07	IFR
5	537290	0.075	0.528	0.0214	IFR
6	537340	3.091	1.231	0.00017	IFR
7	537415	1.52	1.618	1.60E-06	IFR
8	537463	-0.471	0.373	0.14724	DFR
9	537526	0.197	0.908	0.00053	IFR
10	537561	2.757	2.873	1.00E-11	IFR
11	537563	1.98	1.726	1.20E-07	IFR
12	537564	0.26	0.451	0.0938	IFR
13	545002	-0.436	0.798	0.00235	DFR
14	545023	2.423	1.934	2.40E-08	IFR
15	545025	2.783	2.863	1.30E-11	IFR
16	545066	2.986	3.217	5.80E-14	IFR
17	545131	2.512	2.006	1.00E-07	IFR
18	545143	0.154	1.044	0.00018	IFR
19	545152	1.463	2.378	9.20E-09	IFR
20	535205	1.923	1.929	6.60E-07	IFR
21	535209	3.157	3.188	1.10E-12	IFR
22	535210	0.708	0.61	0.03691	IFR
23	535211	1.113	0.896	0.00266	IFR
24	536300	3.886	6.379	5.70E-23	IFR
25.	536493	1.478	1.553	5.50E-06	IFR
26	536504	2.56	2.228	7.60E-09	IFR
27	537384	3.328	2.822	5.60E-11	IFR
28	537400	2.29	1.123	0.00023	IFR
29	545092	0.106	0.89	0.00032	IFR
30	537497	3.588	4.783	1.86E-17	IFR
31	569078	2.657	2.979	4.99E-13	IFR
32	545037	0.609	0.767	0.004	IFR

Table 5.2 Individual System MLEs and LaPlace Statistics

IFR = increasing failure rate, DFR = decreasing failure rate.

Figures 5.1 and 5.2 illustrate the increasing failure rate associated with the pooled values obtained for β and λ. They provide a graphical method for estimating the number of failures as mileage increases for the vehicles. Figure 5.1 shows that the failure intensity increases with age,

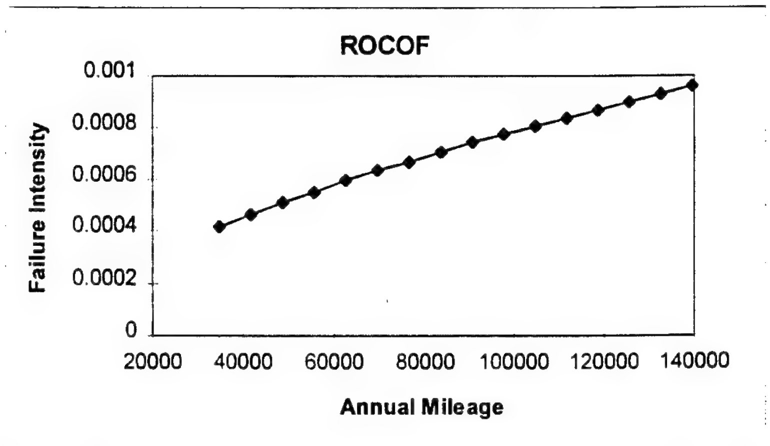

Figure 5.1 Pooled Sample Failure Intensity

and Figure 5.2 shows the expected number of cumulative failures:

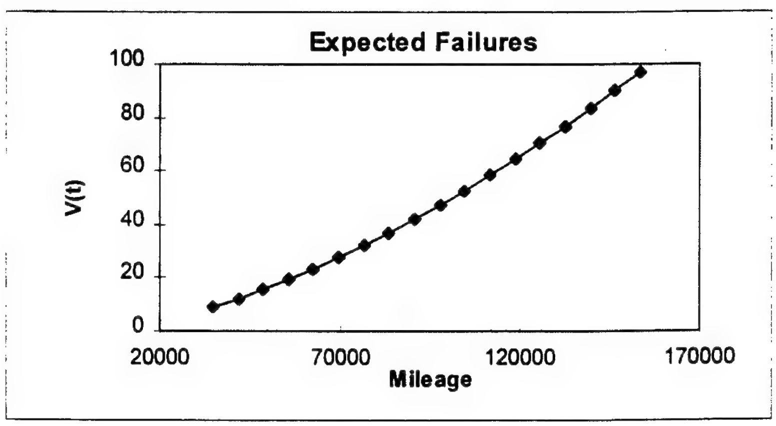

Figure 5.2 Expected Failures

C. COST ANALYSIS OF THE ALTERNATIVES

Cost analysis of the "do-nothing" or overhaul decision alternatives is done using a net-present-value (NPV) comparison of the two estimated maintenance cost streams. For a starting point, a seventeen year *economic useful life* was assumed (USMC, 1994). Assuming that overhaul adds an additional 80% of seventeen years to the present age (i.e., eight years old in 1994), a fourteen year extended life was used as the period for the decision. In other words, the cost-streams would be compared over a fourteen year life, starting in 1994.

1. Assumptions About Input Variables

Cost variables, or factors that derive cost variables, such as annual mileage, were defined as statistical distribution for use with the Crystal Ball add-in. The input variables in the spreadsheet are referred to as *assumption cells* in Crystal Ball. As stated earlier, the distributions for these were derived from empirical cost data from the MIMMS-AIS data files. Reasonable bounds were placed on the ranges of the assumption variables, based on the author's judgement. In most cases, the upper bound was set at three standard deviations for the particular assumption variable, and the lower bound set as the minimum, non-zero value observed in the sample used to derive the assumption variable. Table 5.3 summarizes the input variables and assumptions used for the cost analysis (detailed statistics are provided in Appendix B):

Assumption Variable	Likely Distribution	Parameters
Annual Mileage	Lognormal	μ=6970 miles, σ=7650 miles
Unscheduled Maintenance Cost per ERO	Triangular	Likeliest = $982
Labor Hours per ERO; Unscheduled Maintenance	Triangular	Likeliest = 7.03 hours
Scheduled Maintenance labor hours per ERO	Lognormal	μ= 1.81 hours, σ=1.45 hours^2
Scheduled Maintenance cost per ERO	Triangular	Likeliest = $82
Composite hourly "weighted" labor rate	Triangular	Likeliest = $11.84/hour
Overhaul Costs	Uniform	$23,400 - $32,600
MLE β	Triangular	Likeliest = 1.60

Table 5.3 Input Variable Assumptions

Several difficulties were encountered regarding data for the input variables. First, overhaul costs were difficult to obtain on the HMMWV because of proprietary business data. The Army and Marine Corps Logistics Depots are in competition with each other and private contractors to perform depot level maintenance on equipment. One source (U.S. Army, 1994) provided a range of costs for the HMMWV rebuild vs CUCV re-buy program decision. Another "anonymous" source provided a likely range for rebuild costs. These two estimates together comprise the overhaul cost assumptions. Secondly, since MIMMS-AIS data does not exist for the HMMWV prior to 1990, the *original* reliability and life-cycle maintenance costs could not be determined for use as the "after overhaul" reliability/cost assumptions. Costs are known for the period 1990 to 1994 based on the MIMMS data, but this period was shown to be during the *wearout phase* of the system, therefore these costs may not reflect the reliability of the system over the first eight total years of life. For this reason, the cost relationship used by the U.S. Army (TACOM, 1989) TWVULDP shown in equation (4-3) was used to reflect the maintenance cost after overhaul, starting with time reset to zero. Ideally, the estimated reliability function starting at time equals zero would be used to approximate the maintenance cost-stream after overhaul. Lastly, cost

estimates were not available for a fleet-wide HMMWV replacement, therefore that alternative was not analyzed. In any case, the same approach as in the overhaul alternatives would be used to analyze the *buy-new* option.

2. Assumptions About the Output Forecasts

Forecast Cells are defined as the *output*, or solution cells that are being solved for to assist with decision making. In this case, five forecast cells were defined:

- NPV of the "do-nothing" option.
- NPVs of the cost-streams associated with the 1994, 1996, and 1997 overhaul scenarios. The cost-streams represent the net difference between the cost of overhaul minus the cost of the do-nothing values for each year during the 14 year life-cycle periods.
- Computed value of "Optimal Replacement Interval" (T^*) based on equation (2-18).
- Computed value of the Life Expectancy (L_e) based on equation (2-19).

After the NPV spreadsheet was constructed, the Crystal Ball macro was run for 1,000 iterations. The macro generates statistics for the output or *forecast* cells, and displays forecast histograms. The results of the 1,000 iterations are provided in the "Crystal Ball Report" in Appendix B, but is summarized in Section D to follow.

3. Cost Model Setup

The spreadsheet on page 65 shows the setup of the cost analysis. Input variables are highlighted in **bold** numbers, and appear as the means of the input distributions for the cost assumptions. All other cells are calculated by spreadsheet formulas. The number of critical failures per year is derived by evaluating equation (5-3) over each annual mileage equivalent interval. The NPVs shown on the spreadsheet are computed using the standard method, and represent a fourteen year period. The frequency charts generated by Crystal Ball provide a basis for evaluating the range of values for each of the forecast cells. Note that all of the dollar values appearing on the spreadsheet represent *costs.*

The pooled MLEs shown in Table 5.1 are used to define the ROCOF of the sample, and are used to forecast expected failures in the future. Since the pooled MLE value for β is greater than one, the cumulative number of failures will increase at an increasing rate with usage, thus

causing maintenance costs to increase rapidly. Equation (5-2) gives the pooled estimate of the ROCOF, where:

$$\rho(t) = (5.09 \times 10^{-7})(1.597)(t^{0.597}) \tag{5-2}$$

and the expected number of failures in the interval (t, t+dt) is evaluated as a definite integral,

$$V(t) = (5.09 \times 10^{-7})(t^{1.597})\Big|_{t}^{t+dt} \tag{5-3}$$

Equation (5-3) is used in the spreadsheet cost model (presented in the next section) to forecast the expected number of failures over future annual intervals.

The conversion of mileage to calendar time is done using an annual mileage distribution, discussed in Chapter IV. The mileage distribution was input as an assumption variable for use with the Crystal Ball add-in, and used for calculating values of cells containing mileage figures, such as equation (5-3) above. The value for the mileage used with the do-nothing alternative was rescaled to reflect (annual mileage) x (8 years) so that the resulting expected number of failures would represent the system's actual age. With estimates of the ROCOF and expected failure functions defined, projected maintenance costs can now be forecasted for annual mileage equivalents.

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Category	Mean	Sample Distribution Assumption		
Annual Mileage	6,970	~lognormal		
CM Cost Per ERO $	982.00	~Triangular		
Unsched labor hours/ERO	7.03	~Triangular		
Sched PM labor hours/ERO	1.81	~lognormal		
Sched Maint Costs Per ERO $	82.00	~Triangular		
Discount Rate	6.7%			
Labor Rate (1990)	E3	E4	E5	"Weighted rate"
(composite hourly) $	10.29	$ 12.33	$ 14.46	$ 11.84
β hat	1.597	~Triangular (use LCL=lo to UCL=hi)		
λ hat	4.99E-07	~uniform (use LCL=lo to UCL=hi)		

TACOM Estimate (Annual) =(.0554*Age + .1436)*Mileage + $318

Overhaul Cost $	26,000	~Uniform

T*=	94,913	optimum overhaul interval based on equation (2-29)
Le=	7.3	more years from present based on equation (2-30)

	Year	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
#critical failures:		4	4	4	4	5	5	5	5	6	6	6	6	6	7	7
Do Nothing Alternative		-4,079	-4,381	-4,669	-4,945	-5,211	-5,467	-5,716	-5,957	-6,191	-6,420	-6,642	-6,860	-7,073	-7,282	-7,487
Cumulative		-4,079	-8,460	-13,129	-18,074	-23,285	-28,752	-34,468	-40,425	-46,616	-53,036	-59,678	-66,539	-73,612	-80,894	-88,381
NPV Do nothing	-52,006															
Overhaul in 1994		-27,319	-1,705	-2,091	-2,477	-2,863	-3,250	-3,636	-4,022	-4,408	-4,794	-5,180	-5,953	-6,339	-6,725	-7,111
cumulative costs		-27,319	-29,024	-31,115	-33,592	-36,456	-39,705	-43,341	-47,363	-51,771	-56,565	-61,745	-67,698	-74,037	-80,761	-87,872
NPV 1994 plan	-58,076															
Overhaul in 1996		-4,079	-4,381	-27,319	-1,705	-2,091	-2,477	-2,863	-3,250	-3,636	-4,022	-4,408	-4,794	-5,180	-5,953	-6,339
cumulative costs		-4,079	-8,460	-35,779	-37,484	-39,575	-42,052	-44,916	-48,165	-51,801	-55,823	-60,231	-65,025	-70,205	-76,158	-82,496
NPV 1996 plan	-53,938															
Overhaul in 1997		-4,079	-4,381	-4,669	-27,319	-1,705	-2,091	-2,477	-2,863	-3,250	-3,636	-4,022	-4,408	-4,794	-5,180	-5,953
cumulative costs		-4,079	-8,460	-13,129	-40,448	-42,153	-44,244	-46,721	-49,585	-52,834	-56,470	-60,492	-64,900	-69,694	-74,874	-80,827
NPV 1997 plan	-52,631															
Net difference between Do-nothing and 1994 overhaul	-6,070 0.38% IRR	-23,240	2,676	2,578	2,468	2,347	2,218	2,080	1,935	1,783	1,625	1,462	908	735	557	376
Net difference between Do-nothing and 1996 overhaul	-1,932 4.40% IRR	0	0	-22,650	3,240	3,120	2,990	2,852	2,707	2,555	2,398	2,234	2,066	1,893	1,330	1,148
Net difference between Do-nothing and 1997 overhaul	-625 5.88% IRR	0	0	0	-22,374	3,506	3,376	3,238	3,093	2,942	2,784	2,621	2,452	2,279	2,102	1,534
Cumulative (annual) Miles	48790	55760	62730	69700	76670	83640	90610	97580	104550	111520	118490	125460	132430	139400	146370	153340

The spreadsheet shows four cost streams computed. All figures are expressed as costs. The first is the "do-nothing" alternative, which is calculated for a fourteen year period from the present. The other cost-streams represent performing the overhaul during 1994, 1996 and 1997, respectively. The NPVs of the cost streams are computed for all three alternatives based on OMB Circular A-94 (OMB, 1993) nominal discount rates. Internal Rate of Return (IRR) figures are provided based on the difference between the cost of performing the overhaul and the cost of the do-nothing policy. The IRR is used as a "tie-breaker" between decision alternatives, and provides an idea about the direction in which the costs of the alternatives are moving; i.e., the IRR increases as the overhaul is deferred.

D. ANALYSIS OF RESULTS

The do-nothing alternative is the preferred option by a close margin, based on the static values of the cost estimates for each assumption variable. The NPVs computed for each alternative over the next 14 year period are:

Do-Nothing:	-\$52,006
Overhaul in 1994:	-\$58,076
Overhaul in 1996:	-\$53,938
Overhaul in 1997:	-\$52,631

As the overhaul is deferred into the future, performing the overhaul becomes the preferred alternative, assuming that costs remain constant.

Since each of the cost variables are associated with their own distributions, the forecast values, such as NPV, are all reflected by unique distributions. The probable range and shape of the forecast distribution is generated by simulation. The Crystal Ball simulation was used to run 1,000 iterations to generate the NPVs of the decision alternatives. The *simulation* results validate that deferring the overhaul until after 1997 is preferred, based on the range and measures of central tendency of the alternatives. Results of the simulation are summarized in Table 5.4:

Alternative	IRR	Mean	Median	Mode
Do-Nothing		-$106,633	-$28,200	-$16,363
1994 Scenario	0.4%	-$54,192	-$47,675	-$40,220
1996 Scenario	4.4%	-$51,234	-$46,498	-$38,172
1997 Scenario	5.9%	-$50,429	-$46,448	-$44,694

Table 5.4 Cost Summaries of the Decision Alternatives Based on the Crystal Ball Simulation

The mean value of the cost of the do-nothing alternative ($106,633) is high due to the fact that some high values of β and high annual mileages can be generated based on their distribution shapes, and these are variables in the annual cost equation. Likewise, the median and mode for the do-nothing alternative are relatively low for the 14 year period because the simulation generates mostly low values for the assumption variables mileage, labor-hours, and β. The annual cost equation for the do-nothing alternative is particularly sensitive to the value of β, since it is an exponent and drives the number of expected failures. It is also sensitive to annual mileage, and the cost of overhaul. Cost ranges will be wide due to high variability in the annual mileage. The high cost of overhaul is ultimately the determining factor driving the decision, and since the cost is high, and the cost of the "minimal repairs" maintenance policy does not increase dramatically, the decision alternative favors deferring overhaul into the future.

In comparison, the simulated NPVs increase as the overhaul is deferred into the future. The "static" NPV for the 1997 overhaul cost-stream is nearly identical to the cost of the do-nothing alternative, which implies that the cost-stream for overhaul during or after 1997 is more economical than doing nothing. Although the median and modal values are higher for the simulated overhaul NPVs than the do-nothing alternative, they have less range and variability in annual maintenance costs after overhaul, which leads to more confidence in the decision to perform the overhaul.

1. When to Overhaul?

Unless there are operational reasons to overhaul or upgrade the HMMWV earlier, the optimal time to overhaul is between 1997 and 2001 when the NPV for the overhaul cost-stream begins to be less than the do-nothing cost-stream. Referring to the cost model spreadsheet, the net difference between the NPVs of the overhaul options and do-nothing decreases for each year the overhaul if deferred. After 1997, the net difference between the overhaul and do-nothing alternatives actually becomes a cost savings (which is not shown). The impact of any cost-savings could be significant, since there are over 14,000 HMMWVs in the active fleet. Even marginal savings realized from deferring the overhaul are translated as potentially hundreds of thousands of maintenance dollars for the current fiscal year.

The *rough estimate* life-expectancy calculated from equation (2-19) indicates approximately a seven year period, measured from the present. Further, the optimum overhaul interval calculated by equation (2-18) is also shown in the spreadsheet, and indicates a 93,700 mile interval, measured from time zero. Based on the cumulative annual mileage assumptions, this value represents a period between 1999 and 2001, or seven years from the present. The mean of the optimum overhaul interval based on the simulation was 129,000 miles. The simulation output for these two estimates are provided in Appendix B, and indicate the range and shape of the distributions for these values. The results are summarized in table 5.5:

	Mean	**Median**	**Mode**
Optimal Overhaul Interval (miles)	129,496	89,689	56,583
Life Expectancy (years from present)	7.5	7.0	6.9

Table 5.5 Rough Estimates of Optimal Overhaul Interval and Life Expectancy for the HMMWV

The mileages shown above for the optimal overhaul interval correspond to a period between 1994 and 2005 for the first overhaul, a wide range due to the high variability in annual mileage for different vehicles. The life expectancy values are approximately seven years, measured from the present, which implies that the economic overhaul period is during 2001. Again, it should be emphasized that these two figures are used only as approximations to check assumptions and validate the NPV/Break-even analysis.

2. Which Vehicles Should be Overhauled?

The wide range of overhaul intervals suggests that the fleet should be evaluated on a vehicle-by-vehicle basis, based on annual mileage and the values of β and the LaPlace statistics, as calculated in Table 5.2. Such a table could be automated on a fleet-wide basis, and individual vehicles be nominated as candidates for overhaul/replace each year based on the highest values of these parameters. In other words, vehicles in the worst condition would be flagged, and feedback solicited from owning units regarding their actual condition. The unit commanders (owners) must have the final decision regarding their vehicles, since they are in the best position to know the actual usage, condition and need for overhaul; however, an automated list of vehicles meeting certain criteria would certainly be useful for decision making at the unit level. This process would allow expected program costs to be forecasted several years in advance.

3. Observations About the Sample

Of the 276 unique serial numbers in the sample, only 32 of them had enough recorded failure data available to be able to perform a reasonable trend analysis. It might be argued that a non-random sample may not reflect the entire fleet's reliability posture. In other words, these might simply be the 32 *worst* vehicles in the sample. This is probably not true. There are two responses; first, a significant amount of data was lost or not available during the period of Desert Shield and Desert Storm, therefore a significant amount of failure data is missing. The Deployed Automated Support Centers used to process MIMMS transactions were not fully operational until roughly six months into the deployment, and even after that period, many Marine units did not report into the system due to long distances or lack of communication links with the DFASCs. Secondly, as Chapter III discussed, there are some limitations in the MIMMS-AIS reporting system that do not capture all of the potential failure data. The failure intervals used in the analysis were defined by the *mileages* associated with the EROs. Recall that only one mileage currently is recorded on the ERO, the mileage at failure, therefore failures that occur while the

ERO is open are not captured in MIMMS. Sample statistics on the number of ERO days (measured from open to close dates) was distributed exponentially with a mean of 139 days. Many of these EROs reflected multiple failures.

To support the statement that the 32 vehicles *do* reflect the sample population, a second measure of critical failure intervals is suggested. An alternate definition for a failure interval is the difference between when a part is received and when the *next* part, or a batch of parts is ordered. Presumably the *next* parts are ordered due to a subsequent failure, and it is more administratively convenient to order them using an ERO already open. This measure is suggested because many of the EROs fall into the category of being "perpetually" open, thus, data about when the failures occurred is lost. Assuming that critical parts are ordered roughly the same day that the system fails, and that they are applied the same day they are received, the time between *orders* might be a compromise solution to the data problem. The database used for this analysis consisted of records for 899 unique EROs; 324 of them had four or more "batches" of parts ordered under each ERO. That is, counters were used to total the number of records that had different order dates for batches of parts all recorded on the same ERO. Roughly one third of the EROs represented more than four system "failures" according to this alternative definition.

Another argument is based on trends observed from a fleet-wide perspective. A separate data file provided by the Reliability Analysis Center contained pre-calculated LaPlace trend test statistics (U) for vehicles from the three Regional Activity Centers, representing the entire Fleet Marine Force. After screening out suspect values (based on not enough data available), a file containing 718 unique serial numbers from the most recent update cycle was analyzed. Of those serial numbers, 83% of them had values for U greater than zero, indicating that 83% of the sample exhibited increasing failure rates. The results are summarized in Figure 5.5:

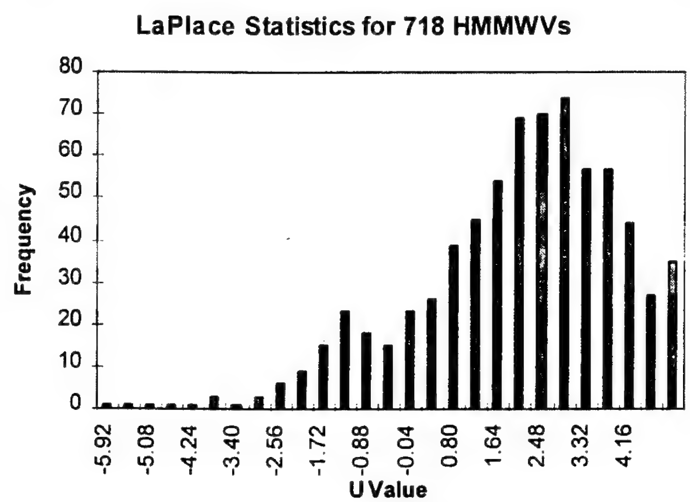

Figure 5.5 LaPlace Values for FMF Sample

Of the 718 vehicles shown in the sample above, 593 of the values are positive, indicating that the sample has an increasing failure rate. These results imply that the majority of the fleet of Marine Corps HMMWVs are in the deterioration phase. Therefore, one might conclude that the vehicle sample reflected by the 32 serial numbers used in this thesis is reflective of the Fleet Marine Force HMMWV status.

4. Limitations

The cost model shown in the spreadsheet is highly simplified, and certain assumptions would need to be refined. For example, the annual maintenance costs after overhaul were computed using the Army's useful life model, however it includes some costs which are not included in the do-nothing maintenance cost model. It was used as the best available data for illustrative purposes. Further, overhaul costs should also be refined and more data obtained prior to making decisions, since the NPV values and IRR are very sensitive to overhaul costs.

E. SUMMARY

This chapter presented a spreadsheet model that calculates pooled and individual values for the parameters of the ROCOF, which are used to forecast the expected number of failures of a sample set of 32 HMMWVs. The pooled MLE for β was roughly 1.6, therefore maintenance costs will increase at an increasing rate. Next, a cost spreadsheet was used to evaluate the decision alternatives using NPV and IRR analysis. The decision alternatives can be better evaluated knowing the probabilities associated with the forecast values, so Monte Carlo simulation was conducted using a spreadsheet add-in program called Crystal Ball. The Crystal Ball results indicated that the economic overhaul period consisted of a range of values starting in approximately the year 1997 for the HMMWV fleet. Specific vehicles can be nominated for overhaul based on their condition, which can be described by the values of β and the LaPlace test statistic (U). By calculating fleet-wide trend statistics, "blocks" of vehicles can be programmed for overhaul with several years lead-time.

VI. CONCLUSION AND RECOMMENDATIONS

A. SUMMARY

Economic overhaul or replacement intervals can be approximated based on adequate maintenance data. The necessary data elements needed to use the approach in this thesis are maintenance costs and failure times. If the pattern of time between failures indicates an increasing failure rate, then the maintenance costs will increase rapidly, as a function of the failure intensity. The main variables affecting the replacement/overhaul decision are the failure intensity and the cost. As the exponent (β) of the ROCOF increases, deterioration occurs more rapidly and *minimal repair* costs escalate. Net present value analysis helps to identify the economic replacement period. In the case example in the last chapter, NPVs were calculated for scenarios that represented alternative overhaul options. The results of the NPV analysis indicated that the overhaul should be performed between 1997 and 2001. The main limitation of the approach is the validity of the failure data. However with adequate screening, the heuristic techniques presented in Chapter III can eliminate the majority of the invalid data before the actual analysis is performed.

The approach to estimating the ROCOF outlined in this thesis is repeatable, and lends itself to an automated process. With the exception of the overhaul costs and equipment inventory data (manufacturing date, fielding dates), all of the data was extracted through the maintenance management database. For the Marine Corps equipment, the MIMMS database is used, and for Army equipment, the TACOM Sample Data Collection can be used. The MIMMS data for the HMMWV was downloaded from mainframe computer files, and all of the subsequent queries, computations and simulation were done with a spreadsheet program on a personal computer.

B. CONCLUSION

Reliability theory can be effectively combined with cost analysis to assist with overhaul or replacement policy decisions. The Weibull intensity function adequately describes the material condition of equipment, either on an individual or fleet-wide basis. From the failure intensity, simulation can be used to forecast expected failures over annual equivalent operating times, in order to estimate the associated costs of failures. Overhaul or replacement decisions are analyzed using NPV, break-even and internal rate of return analysis to derive the policy decisions. The

model presented in this thesis is straightforward in that it is repeatable on a broad basis and lends itself to analysis of entire fleets of systems. By incorporating reliability theory into program cost decisions, the impacts of replacing or overhauling a type of system too early can be evaluated in more detail, and more economical decisions can be made.

C. RECOMMENDATIONS

1. Design Changes to the Maintenance Management Information System

Future design changes to the MIMMS-AIS or its next generation (PC ATLASS) should include a method for capturing meter readings *at each failure*, even if multiple failures occur during the administrative life of the ERO. The ERO form itself presently allows only for input of the meter reading *at restoration*. Dhillon (1988) includes *date of failure* as a crucial, yet basic element of failure data collection required for valid reliability analysis. A critical failure is defined as a condition in which the system became not operational or mission capable, due to the failure of a component, and the time of the failure event would have to be translated into straightforward terms applicable to data entry. This would be relatively simple to implement; it would involve recording the meter reading of the system when certain status change transactions are input. Maintenance status changes are already being routinely captured in MIMMS-AIS. The additional input entry (meter reading) along with the status change transaction should not pose a significant burden on the maintenance shops. The *cost* of collecting the additional data should not be significant, since the mechanics or technicians working on the equipment usually have to physically record other maintenance tasks on the source documents. By recording the mileage at failure, the problems discussed in Chapter III, i.e., long maintenance cycle times, multiple EROs, and single mileages *at restoration*, would be solved.

2. Maintain Reliable Maintenance Data on Combat Essential Equipment

Much like the U.S. Army's Sample Data Collection program, the Marine Corps should track a sample of specific principal end-items throughout their life-cycle. For combat critical equipment systems, called *pacing items*, a representative sample of them should be closely monitored through data reliability programs at selected units. Instead of archiving inactive maintenance data on these specified items, automated records should be centrally maintained for analysis such as the one presented in this thesis. The cost of data storage on a select sample would not be as prohibitive as for the entire inventory.

The recommended list of items is contained in the current edition of the Marine Corps Bulletin 3000 series directives (MCBul 3000, 1994). A sufficient number of principal end-items should be derived statistically for each separate system in the program. Unit maintenance shops that maintain the selected equipment would be provided with special instructions, and given incentives to report accurately on the equipment. In short, a representative sample of equipment, tracked throughout its life-cycle in a controlled data collection setting could alleviate some of the reporting difficulties presently experienced with analyzing raw MIMMS-AIS data. Better input data will lead to more conclusive results for program decisions.

3. Track Equipment Status After Overhaul

Depot level maintenance production is done in batches, and no centralized records are currently kept regarding specific items overhauled. Consequently, valid data does not exist except at the unit level, regarding the status of Marine Corps equipment after rebuild, IROAN or ESP. There is no way to measure the effects of overhaul on reliability or the extent of life extension without such data. It is recommended that the equipment identified for the "data reliability program" described above also be specifically tracked after rebuild or ESPs are performed in order to measure the effectiveness of the overhaul program. In some cases the Army has found that vehicles were actually worse off after rebuild than before (Lee, Puzzuoli and Hoogterp, 1975).

4. Periodic Status Reviews

A periodic review of the principal end items described above should be conducted to validate program plans. The values of β and the LaPlace statistic for the individual vehicles shown in Table 5.2 provide a qualitative description of the material condition of a sample of equipment systems. Such a table could be automated and generated for the entire fleet or for the controlled sample described above. Table 4.1 provides interpretations that can be used to quickly obtain a picture of the fleet based on the values of these two parameters. This approach quantifies measures of deterioration that are otherwise estimated by intuition. While it is not a substitute for good intuition, it is another element of information to support decision making. As the general trends of these values change, the data should be compared against alternative policies, on the basis of program priority and the essentiality of the combat system.

5. Evaluate Causes of Data Entry Problems

Further study should be done to identify problems with data entry. For example, accurate reporting may be too difficult in terms of busy shop operations, therefore short-cuts and work-arounds become the routine. A lack of user-friendliness or tedious input processing procedures may also be reasons for inaccurate data. Ongoing, quality training of maintenance management supervisors, shop supervisors and clerks should be emphasized at all levels. A Total Quality Leadership approach to improving the maintenance data input could be implemented at over the organizational spectrum from the small shop to the HQMC Maintenance Policy section level.

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APPENDIX A. SPREADSHEET FORMULAS AND LOGIC FLAGS

A. PURPOSE

This Appendix provides the spreadsheet formulas used in Microsoft Excel to analyze the MIMMS-AIS data. Formulas are needed to convert certain data values, make to comparisons between selected fields, or to flag specified criteria. The left column represents the spreadsheet column in which the field name appears, and is provided only as reference for the cell addresses described in the formulas. Data records appear as rows in the spreadsheet. Fields identified with a "D" indicate data fields compiled directly from the "raw" database. If the field is a data type, the field description and number of characters (n) is provided. All other fields are defined by a spreadsheet formula. Fields identified with a "C" stand for "counter" or computed value, and "L" stands for "logic" field.

To use the formulas in the spreadsheet, the database is first read into a new spreadsheet. Columns are inserted into the database, as required. The formulas are input into the first blank row under the header, and then copied down the entire range of rows containing data.

	FIELD NAME		VALUE or FORMULA (# characters)	DESCRIPTION
A	RAC	D	Alpha-numeric (6)	Regional Activity Code
B	SERIAL #	D	Numeric (6)	USMC Registration number of the vehicle
C	ERO	D	Alpha-numeric (5)	Equipment Repair Order
D	METER	D	Numberic (10)	Primary Meter Reading; equipment operating time

	FIELD NAME		VALUE or FORMULA	DESCRIPTION
E	FLAG 1	L	=IF(B2=B1,IF(C2=C1,1,0),2)	Compares the serial number and ERO number in previous record. "0" = both are same; "1"= unique ERO, "2"= unique serial
F	FLAG 2	L/ C	=IF(E2=1, IF(H1<H2,"LOOK",1),0)	Checks if the next unique ERO was closed prior to an older ERO being closed.
G	DATERECIN	D	Numeric (5)	Date the ERO was opened.
H	DATECLOSED	D	Numeric (5)	Date the ERO was closed.
I	MILABHRS	D	Numeric (5)	Total direct labor hours expended on the ERO.
J	DLHOURS	C	=I2/10	Necessary conversion, due to decimal placement of MILABHRS.
K	DATEORDERED	D	Numeric (5)	Date part was requisitioned.
L	DTRCVDCANC	D	Numeric (5)	Date part was received at the unit.
M	ORDR YEAR	C	=VALUE(LEFT(K2,2))	Julian date conversion to numeric value for subtraction or comparison of dates.
N	ORDR DAY	C	=VALUE(RIGHT(K2,3))	Julian date conversion.
O	REC YEAR	C	=VALUE(LEFT(L2,2))	" "

	FIELD NAME		VALUE or FORMULA	DESCRIPTION
P	REC DAY	C	=VALUE(RIGHT,L2,3))	" "
Q	ΔREQ LAG	C	=IF(O2=M2,P2-N2,IF(O2= M2+1), ((365-N2)+P2), IF(O2=M2+2),((365-N2)+P2), IF(O2= M2+3),((365-P2)+N3+365))))	Used to subtract the order date of the part from the received date to compute delivery delay time.
R	ΔNEXT REQ	C	=IF(O2=M3,N3-P2, IF(O3= M2+1), ((365-P2)+N3), IF(O3=M2+2), ((365-P2)+N3), IF(O3= M2+3),((365-P2)+N3+365))))	Used to compute the difference between the received date of the current part and the order date to the next part. Could be a second measure of time between failures.
S	NEXT REQ	C	=IF(S2<=1,R2," ")	If the ΔNEXT REQ is negative, leave blank, else write the value of the difference in order days. Used to construct histogram.
T	PARTNAME	D	Character (19)	Description of the part being ordered.
U	PARTSCHG	D	Numeric (11)	Cost of the part.
V	PCOSTS	C	=(U2*AA2)/100	Cost time quantity; and adjustment due to decimal placement of PARTSCHG.
W	CUML ERO$	C	=IF(E2=0,V2+V1,V2)	Accumulates parts costs for unique EROs.

	FIELD NAME		VALUE or FORMULA	DESCRIPTION
X	ERO COST	C	=IF(E2=2,W2, IF(E3≥1,W2, " "))	Shows ERO total parts costs adjacent only to the last record for each unique ERO number. Blank space otherwise.
Y	CUMLSER#	C	=IF(B2=B1,V2+V1,V2)	Accumulates parts costs for each unique serial number
Z	SER#COST	C	=IF(E3=2,Y2," ")	Shows vehicle total parts costs adjacent only to the last record for each unique serial number.
AA	QTY	D	Numeric (3)	Quantity of the part being ordered.
AB	ECH	D	Numeric (3)	Echelon of repairs; level of maintenance
AC	FAILCOUNT	C	=IF(E3≥1,1,0)	First step of a counter used to accumulate the number of critical failures recorded for a unique serial number. Value of "1" is a placeholder to start the count.
AD	#FAILURES	C	=IF(E3=1,H2+1,1)	Accumulates the number of failures for a serial number.

* Syntax for the "IF" statement in Microsoft Excel is: "=IF(condition, then_, else_)." Nested IF statements imply a boolean "AND" relationship for the criteria specified.

APPENDIX B. DATA ANALYSIS RESULTS

A. GRAPHICAL FAILURE PLOT

Chapter IV introduced the concept of trend testing in reliability analysis. Failure plotting is one of the methods described to evaluate the material condition of a complex repairable system. Figure A.1 provides a graphical representation of the trends in the failure patterns of the actual data presented in Chapter V. All 32 vehicle data sets are not shown, rather a sample of four representative HMMWV serial numbers to illustrate the general appearance of the curves.

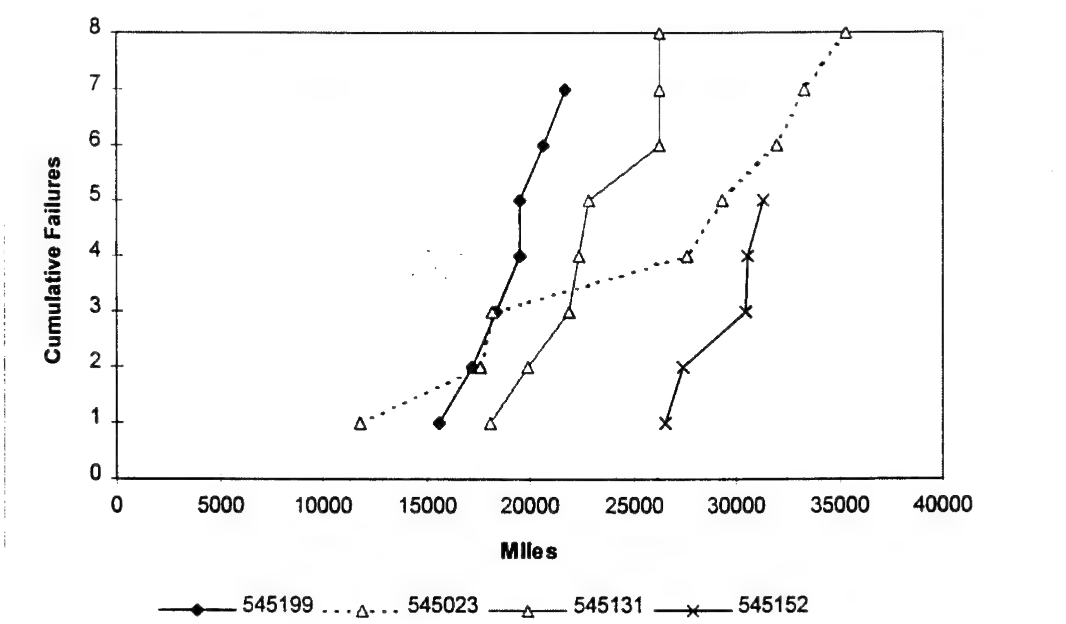

Figure 4.1 Cumulative Failure Mileage for Four HMMWVs (four vehicle serial numbers are shown)

B. SYSTEM FAILURE DATA

The data below represent to total time to system failure for each of the vehicles analyzed in the case study. It was obtained by identifying vehicles that had six or more recorded failures in the data sample. For each vehicle that met this criteria, their mileages were copied into the MLE estimation worksheet presented in the next section.

Serial numbers are **bold** followed by the mileages at failure:

535199	**535212**	**535393**	**537144**	**537290**	**537340**	**545191**	**537415**
15649	9890	18312	9632	9974	13493	2929	6545
17214	12012	17212	12292	11200	13561	7042	9781
18337	12331	20097	13478	9875	17139	7043	12166
19524	12035	21454	13479	13837	17738	7732	12184
19527	15266	22563	15652	19899	18154	8471	12714
20713	15937	24317	13920		18304		14627
21712	17330	25682	13920		18480		18130
			16334				
			17579				

537463	**537526**	**537561**	**537563**	**537564**	**545002**	**545092**	**545023**
9679	10379	1786	7900	15668	15470	3256	11764
9707	12810	9105	14297	15670	17225	9374	17666
10102	15488	9117	20054	17456	17225	16015	18170
10135	21772	9195	22739	18476	19813	18779	27601
13175	24767	9970	31053	18876	20129	23007	29330
29756	24861	13445	34280	22454	20224	54632	31966
30150	39725				22655		33330
					34092		35322

545025	**545066**	**545131**	**545143**	**545152**	**535200**	**545037**	**535204**
27835	4837	18134	8943	26566	13462	11002	21094
28469	17370	19946	14446	27394	17603	11520	21099
29105	19239	21872	15182	30445	17603	12173	21261
29173	20174	22418	16324	30571	18248	15897	23462
29272	21038	22817	16479	31289	19709	19183	23453
21038	26301	26294	17008		19820		27305
32766		26301	30654				
		26302					

535205	**535209**	**535210**	**535211**	**536300**	**536493**	**537567**	**536504**
17030	12787	16184	12584	6458	9572	12417	9100
18638	16691	16193	12383	9354	11468	14058	1288
18846	19005	17234	13421	9393	12767	15376	12235
19163	19722	17695	14060	9950	13193	16096	16753
19269	21818	17989	16901	10274	14428	16402	17002
20724	22029	19289	16909		14896	24689	18168
					17270		

537384	537400	537497
17763	19801	14306
19670	20000	16891
24108	24039	17738
24733	25163	17935
24797	26742	18510
	27009	

C. MLE ESTIMATION WORKSHEET

The next page contains an extract of the MLE estimation worksheet used to for the data shown above. Prior to copying the $TTSF_i$ data into the MLE worksheet, the $TTSF_i$s were sorted in ascending order to properly reflect mileages that increase. Reasons for the data being in non-sorted sequence stems from the fact that the source database was sorted by serial number, then date-received-in-shop, then date closed, prior to the analysis. For this reason, some of the mileages appear out of sequence in the raw data.

Subtotals for the various columns appear below the cells for each serial number, grand totals for the subtotal rows appear in the upper left corner of the spreadsheet. Values for the individual vehicle MLEs β and λ as well as the LaPlace test statistic based on equations (2-12), (2-13) and (2-9), respectively appear in the boxes for each system. The pooled MLEs appear in the box at the top of the spreadsheet, and are based on equations (2-12) and (2-13). Only calculations for the first two vehicles are shown.

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DATA TOTALS:	
Σ Nq:	157
Σ ln(TTSFi)	1879.54
Σ TTSFi^β	3.15E+08
Σ ln(TTSFn/TTSFi)	9.83E+01

		LCL	UCL
β hat:	**1.597**	**1.393**	**1.812**
λ hat:	**4.99E-07**	**4.35E-07**	**5.7E-07**

1

535199

LaPlace:	2.038
β=	1.85
λ=	6E-07

Time to System Failure (i)	TTSFi	scaled TTSFi	i	ln(TTSFn/TTSFi)	ln(TTSFi)	TTSFi^β
1	15649				9.658	4975029
2	17214	1565	1	1.354	9.753	5792767
3	18337	2688	1	0.813	9.817	6407761
4	19524	3875	1	0.448	9.879	7082681
5	19527	3878	1	0.447	9.880	7084419
6	20713	5064	1	0.180	9.939	7783742
7	21712	6063	1	0.000	9.986	8391685
8						
9						
10						
Σ(Ni)			6			
Σ ln(TTSFn/TTSFi)				3.242		
Σ ln(TTSFi)					68.91	
Σ TTSFi^β						8391685

2

535212

LaPlace:	1.452
β=	1.448
λ=	1.49E-05

TTSFi	scaled TTSFi	i	ln(TTSFn/TTSFi)	ln(TTSFi)	TTSFi^β
9890				9.199	2391192
12012	2122	1	1.255	9.394	3261336
12331	2441	1	1.114	9.420	3400707
12035	2145	1	1.244	9.396	3271311
15266	5376	1	0.325	9.633	4782053
15937	6047	1	0.207	9.676	5122010
17330	7440	1	0.000	9.760	5855215
		6			
			4.145		
				66.48	
					5855215

** 31 Additional "boxes" for the system computations appear on the rest of the spreadsheet ->

D. SIMULATION OUTPUT

The following pages contain the simulation output generated by the "Crystal Ball" software. The *assumption* cells are input variables that represent the costs, mileage and labor hour calculations used in the cost model. The *forecasts* are shown as probability distributions of the resulting equations.

Simulation Forecasts

Forecast: NPV Do-nothing cost-stream over 14 year period

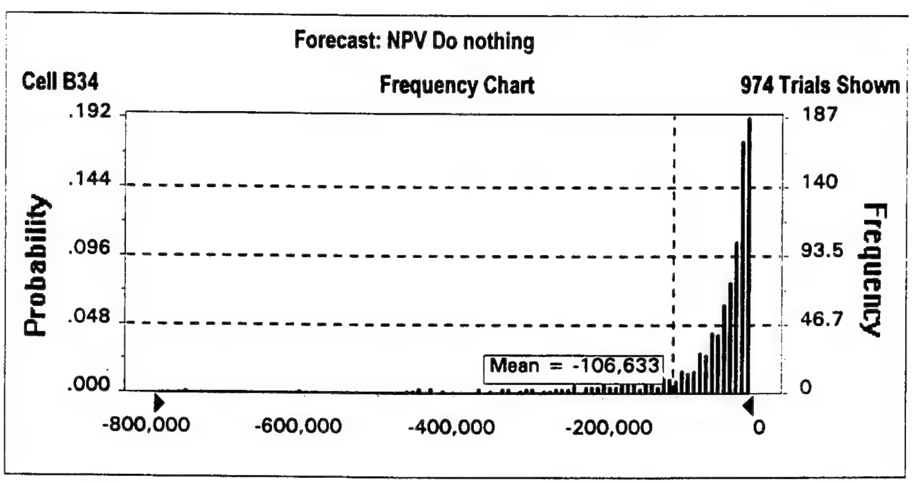
Summary:

Display Range is from -800,000 to 0

Entire Range is from -2,902,079 to -1,862

After 1,005 Trials, the Std. Error of the Mean is 7,663

Statistics:	Value
Trials	1005
Mean	-106,633
Median (approx.)	-28,200
Mode (approx.)	-16,363
Standard Deviation	241,781
Variance	5.85E+10
Skewness	-5.11
Kurtosis	38.05
Coeff. of Variability	-2.27
Range Minimum	-2,902,079
Range Maximum	-1,862
Range Width	2,900,217
Mean Std. Error	7,626.74



Forecast: NPV 1994 plan

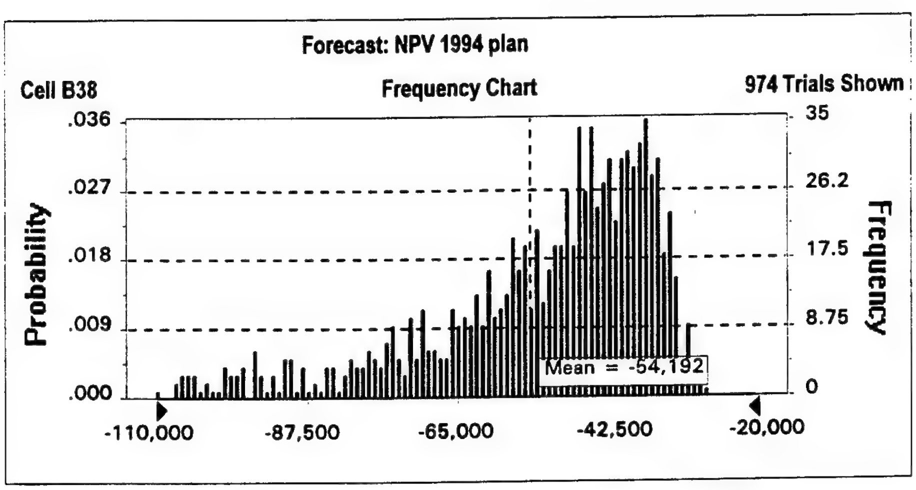
Summary:

Display Range is from -110,000 to -20,000

Entire Range is from -138,080 to -27,503

After 1,005 Trials, the Std. Error of the Mean is 656

Statistics:	Value
Trials	1005
Mean	-54,192
Median (approx.)	-47,675
Mode (approx.)	-40,220
Standard Deviation	20,705
Variance	4.29E+08
Skewness	-1.53
Kurtosis	5.14
Coeff. of Variability	-0.38
Range Minimum	-138,080
Range Maximum	-27,503
Range Width	110,576
Mean Std. Error	653.11



Forecast: NPV 1996 plan

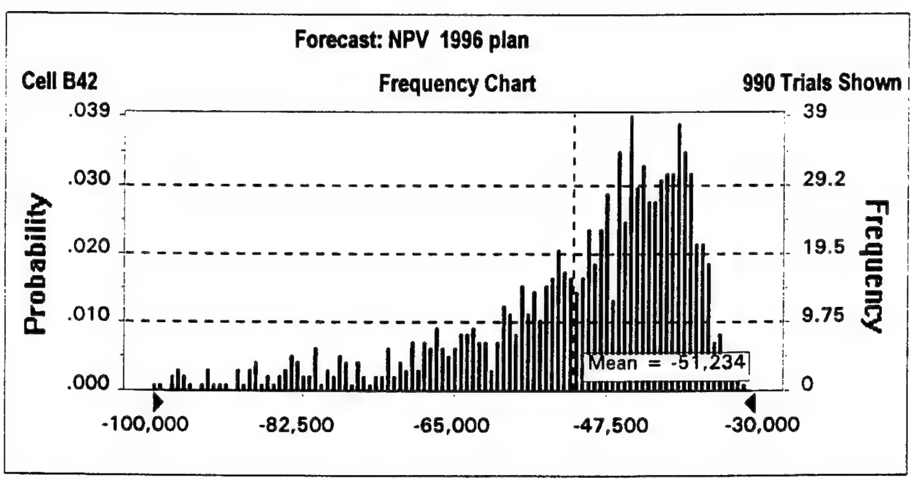
Summary:

Display Range is from -100,000 to -30,000

Entire Range is from -112,617 to -31,256

After 1,005 Trials, the Std. Error of the Mean is 481

Statistics:	Value
Trials	1005
Mean	-51,234
Median (approx.)	-46,498
Mode (approx.)	-38,172
Standard Deviation	15,169
Variance	2.30E+08
Skewness	-1.52
Kurtosis	5.13
Coeff. of Variability	-0.30
Range Minimum	-112,617
Range Maximum	-31,256
Range Width	81,362
Mean Std. Error	478.49



Forecast: NPV 1997 plan

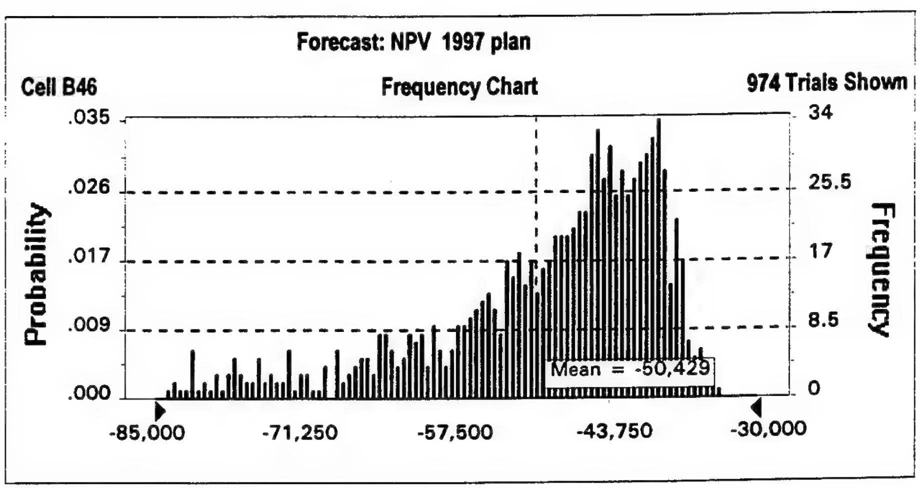
Summary:

Display Range is from -85,000 to -30,000

Entire Range is from -102,161 to -33,339

After 1,005 Trials, the Std. Error of the Mean is 406

Statistics:	Value
Trials	1005
Mean	-50,429
Median (approx.)	-46,448
Mode (approx.)	-44,694
Standard Deviation	12,797
Variance	1.64E+08
Skewness	-1.52
Kurtosis	5.12
Coeff. of Variability	-0.25
Range Minimum	-102,161
Range Maximum	-33,339
Range Width	68,822
Mean Std. Error	403.66

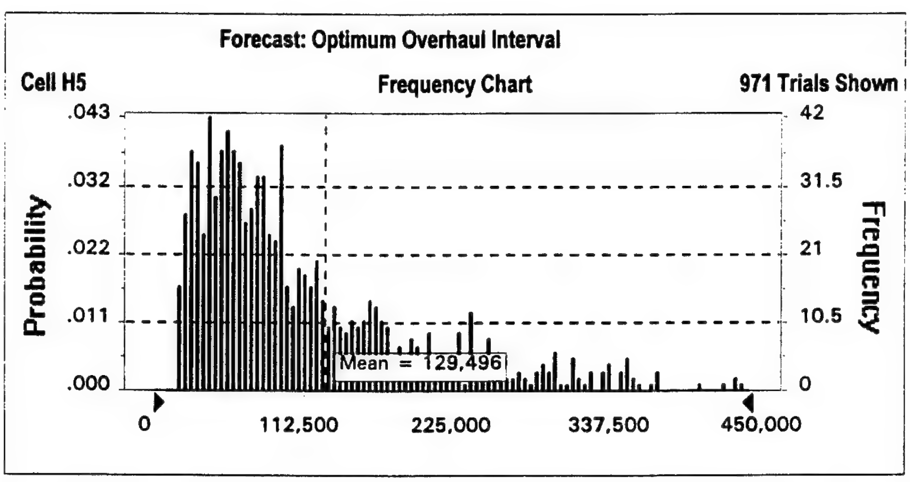


Forecast: Optimum Overhaul Interval (miles)

Summary:

Display Range is from 0 to 450,000
Entire Range is from 19,340 to 846,974
After 1,005 Trials, the Std. Error of the Mean is 3,837

Statistics:	Value
Trials	1005
Mean	129,496
Median (approx.)	89,689
Mode (approx.)	56,583
Standard Deviation	121,078
Variance	1.47E+10
Skewness	2.50
Kurtosis	10.84
Coeff. of Variability	0.93
Range Minimum	19,340
Range Maximum	846,974
Range Width	827,635
Mean Std. Error	3,819.29



Forecast: Life Expectancy (from present)

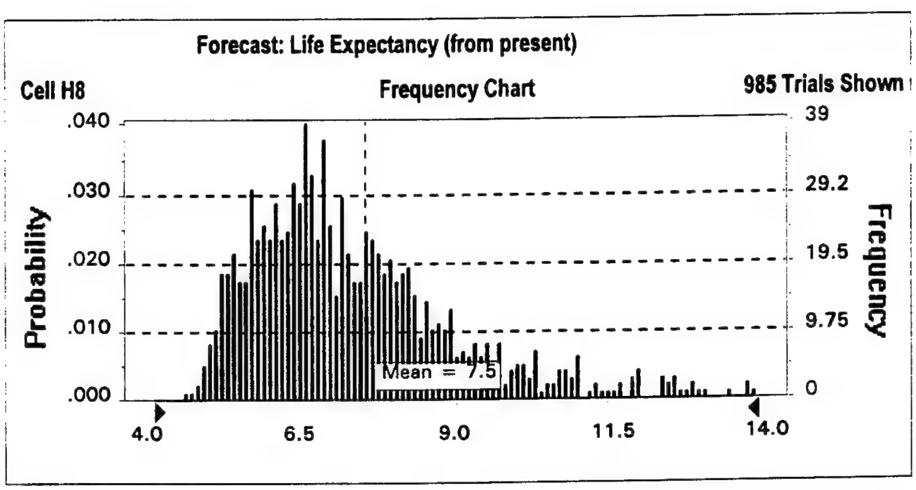
Summary:

Display Range is from 4.0 to 14.0

Entire Range is from 4.5 to 24.7

After 1,005 Trials, the Std. Error of the Mean is 0.1

Statistics:	Value
Trials	1005
Mean	7.5
Median (approx.)	7.0
Mode (approx.)	6.9
Standard Deviation	2.1
Variance	4.6
Skewness	2.37
Kurtosis	12.67
Coeff. of Variability	0.28
Range Minimum	4.5
Range Maximum	24.7
Range Width	20.2
Mean Std. Error	0.07



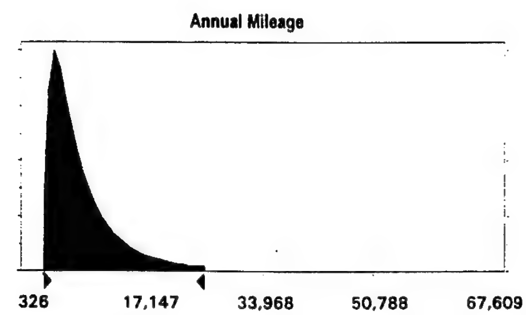
Assumptions About Input Variables

Assumption: Annual Mileage

Lognormal distribution with parameters:

Mean	6,970
Standard Dev.	7,650

Selected range is from 500 to 25,000
Mean value in simulation was 5,882

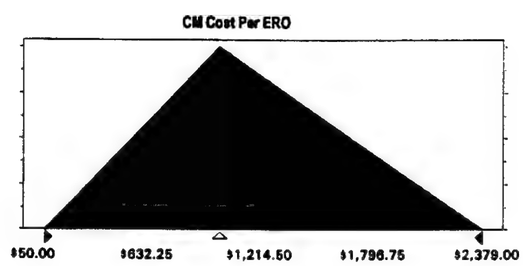


Assumption: CM Cost Per ERO

Triangular distribution with parameters:

Minimum	$50.00
Likeliest	$982.00
Maximum	$2,379.00

Selected range is from $50.00 to $2,379.00
Mean value in simulation was $1,128.26

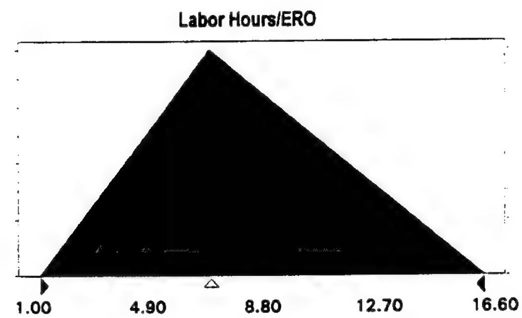


Assumption: Labor Hours/ERO

Triangular distribution with parameters:

Minimum	1.00
Likeliest	7.03
Maximum	16.60

Selected range is from 1.00 to 16.60
Mean value in simulation was 8.12

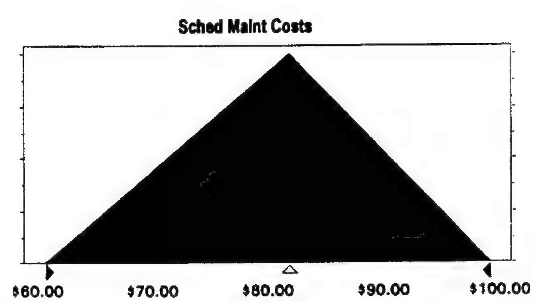


Assumption: Sched Maint Costs

Triangular distribution with parameters:

Minimum	\$60.00
Likeliest	\$82.00
Maximum	\$100.00

Selected range is from \$60.00 to \$100.00
Mean value in simulation was \$80.42

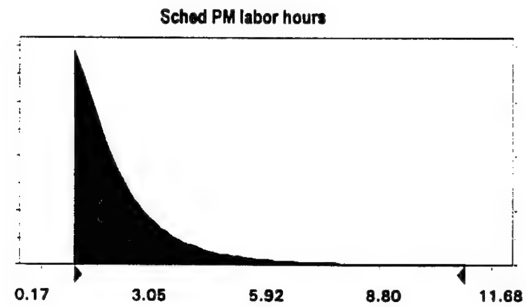


Assumption: Sched PM labor hours

Lognormal distribution with parameters:

Mean	1.81
Standard Dev.	1.45

Selected range is from 1.00 to 11.00
Mean value in simulation was 2.32

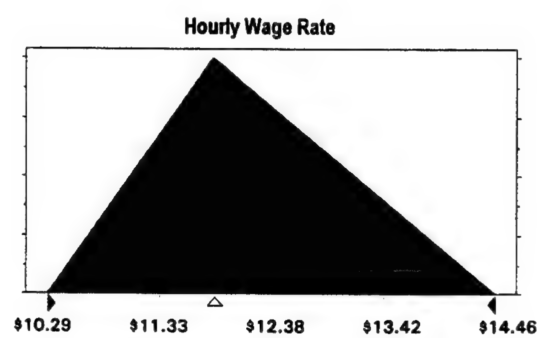


Assumption: Hourly Wage Rate

Triangular distribution with parameters:

Minimum	$10.29
Likeliest	$11.84
Maximum	$14.46

Selected range is from $10.29 to $14.46
Mean value in simulation was $12.16



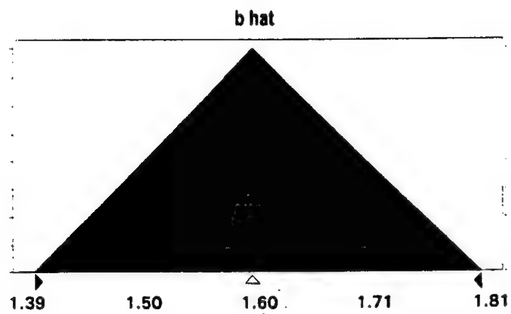
Assumption: b hat

Triangular distribution with parameters:

Minimum	1.39
Likeliest	1.60
Maximum	1.81

Selected range is from 1.39 to 1.81

Mean value in simulation was 1.60

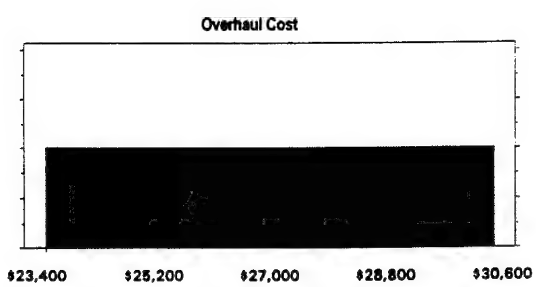


Assumption: Overhaul Cost

Uniform distribution with parameters:

Minimum	$23,400
Maximum	$30,600

Mean value in simulation was $26,981



APPENDIX C. PARETO ANALYSIS OF PARTS USAGE

A. PURPOSE

This Appendix provides the results of the Pareto analysis of the HMMWV parts usage for the entire database sample. Only the first 55 items are shown, the remaining parts consists of less than 0.3% of the total usage over the 54 month sample period. Percentages reflect parts *usage*, i.e., as a percentage of the total demand quantity, not costs.

The purpose of the Pareto analysis was to establish that the HMMWV is a sufficiently complex system, such that no single item contributes to the majority of the system failures. In the author's opinion, the one questionable item (glow plugs) that amounts to sixteen percent of the total usage was most likely attributable to Operation Desert Storm. The sandy, dusty environment, coupled with the fact that JP-5 aviation fuel was used in the HMMWVs caused widespread fuel injector clogging. Many Marine units began replacing fuel injectors on a preventative basis. The fuel injector problem was mainly isolated to Desert Storm usage.

The low percentages for the remaining parts indicates that none of the rest of the parts contribute to a significant amount of the usage, therefore it is assumed that the HMMWV is sufficiently complex to use the model presented in this thesis.

PART NAME Total Sum of PARTCOST	TOTAL COST $761,926	% USAGE	CUML %	QTY 7281
GLOW PLUG	768.40	16.26%	16.26%	1184 A
LAMP,INCANDESCENT	4,343.35	7.03%	23.29%	512 A
TIRE,PNEUMATIC	24,001.00	6.32%	29.61%	460 A
BATTERY,STORAGE	10,414.04	5.10%	34.71%	371 A
DISK BRAKE SHOE	333.60	2.84%	37.55%	207 A
PARTS KIT,BALL JOIN	2,584.27	2.82%	40.37%	205 B
PACKING,PREFORMED	172.64	2.79%	43.15%	203 B
TIE ROD END,STEERIN	3,901.49	2.61%	45.76%	190 B
STARTER,ENGINE,ELEC	54,096.00	2.31%	48.07%	168 B
ROTOR,DISC BRAKE	1,335.96	2.05%	50.12%	149 B
CUSHION,SEAT,VEHICU	3,698.15	1.91%	52.03%	139 B
COIL,ELECTRICAL	3,594.50	1.90%	53.92%	138 B
NOZZLE,FUEL INJECTI	641.52	1.88%	55.80%	137 B
PARTS KIT,HAND BRAK	2,308.26	1.73%	57.53%	126 B

PART NAME	TOTAL COST	% USAGE	CUML %	QTY
TERMINAL,LUG	83.16	1.68%	59.21%	122 B
CONTROL,REMOTE SWIT	12,154.00	1.65%	60.86%	120 C
CUSHION,SEAT BACK,V	2,012.05	1.59%	62.45%	116 C
LUBRICANT,RUN FLAT	78.05	1.51%	63.96%	110 C
FILTER,FLUID	151.51	1.50%	65.46%	109 C
SEAL,NONMETALLIC SP	229.32	1.44%	66.90%	105 C
STEERING GEAR	9,135.00	1.19%	68.10%	87 C
PUMP ASSEMBLY,POWER	3,417.85	1.17%	69.26%	85 C
MOTOR,WINDSHIELD WI	19,690.92	1.15%	70.42%	84 C
GLASS,LAMINATED	1,071.33	1.14%	71.56%	83 C
FLYWHEEL,ENGINE	1,771.45	0.99%	72.54%	72 C
MIRROR ASSEMBLY,REA	3,703.65	0.96%	73.51%	70 C
HOSE,AIR DUCT	221.75	0.96%	74.47%	70 C
CONTROL ASSEMBLY,PU	1,177.64	0.93%	75.40%	68 C
BLADE,WINDSHIELD WI	139.20	0.93%	76.34%	68 C
BELTS,V,MATCHED SET	347.17	0.87%	77.20%	63 C
SCREW,SELF-LOCKING	9.20	0.84%	78.04%	61 C
CLAMP,HOSE	7.26	0.84%	78.88%	61 C
PUMP,FUEL,METERING	31,980.00	0.82%	79.70%	60 C
TRANSFER TRANSMISSI	63,189.00	0.81%	80.51%	59 C
SPRING,HELICAL,TORS	29.40	0.76%	81.27%	55 C
TRANSMISSION,HYDRAU	103,356.00	0.74%	82.01%	54 C
FILTER ELEMENT,INTA	834.36	0.70%	82.71%	51 C
GASKET	35.59	0.69%	83.40%	50 C
VALVE,PNEUMATIC TIR	4.80	0.67%	84.07%	49 C
SWITCH,THERMOSTATIC	1,041.55	0.65%	84.71%	47 C
NUT,SELF-LOCKING,HE	8.14	0.58%	85.29%	42 C
IMPELLER,FAN,AXIAL	7,585.00	0.56%	85.85%	41 C
HOOD,ENGINE COMPART	14,782.00	0.52%	86.38%	38 C
HORN,ELECTRICAL	882.08	0.51%	86.88%	37 C
INSTALLATION AND EQ	180.38	0.47%	87.35%	34 C
HOSE,PREFORMED	124.00	0.45%	87.80%	33 C
SCREW,CAP,HEXAGON H	44.06	0.41%	88.22%	30 C
FITTING,LUBRICATION	0.75	0.41%	88.63%	30 C
ENGINE,DIESEL	170,404.00	0.40%	89.03%	29 C
HALFSHAFT ASSEMBLY	3,008.00	0.40%	89.42%	29 C
SWITCH,SAFETY,NEUTR	437.67	0.37%	89.80%	27 C
SHROUD,FAN,RADIATOR	880.36	0.36%	90.15%	26 C
PARTS KIT,UNIVERSAL	216.10	0.36%	90.51%	26 C
STRIKE,CATCH	5.76	0.36%	90.87%	26 C

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